Consumer Credit Scoring
An empirical study involving home loans within the Nepalese banking sector

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Abstract

Nepalese banks have witnessed a considerable shift in recent years towards its loans and advances by focussing on consumer credit. The traditional method of evaluating applicants that is based on the judgmental system is increasingly becoming inappropriate for the large volume of applicants. As a result of the shift in the lending market and the increased emphasis placed by the regulator on risk management, Nepalese banks have to rethinking on the way they assess their applicants for credit.

Traditionally, the credit decision whether to accept/reject an applicant has been based on the subjective evaluation of the credit application forms and supporting documents. The literature advocates an objective approach on the lines of credit scoring which is fast, reliable, consistent and risk-based. On the strengths of this argument, this thesis presents the qualitative and quantitative considerations including issues relating to data capture, model development and implementation of a formal credit scoring model within the Nepalese Banking sector.

The questionnaire was administered with the non-managerial level staff, the respondents in the expert interviews were managerial level staff and the database for model development were taken from a home loans customer database of a typical Nepalese bank. The findings of this work point to the fact that it is possible to develop such an objective model using six key characteristics and jointly produce a model that will predict the quality of loan with an acceptable degree of confidence.

Key Words: Consumer Credit, Credit Risk, Credit Scoring, Home Loans, Logistic Regression.

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List of Abbreviations

BIS- Bank of International Settlements
BCBS- Basel Committee on Banking Supervision
Cs- Character, Capital, Collateral, Capacity and Condition
CD- Credit Deposit
CA- Capital Adequacy
CAMELS- Capital Adequacy, Asset Quality, Management Aspects, Earnings, Liquidity and Sensitivity to Market Risk
CAMPARI- Character, Ability, Margin, Purpose, Amount, Repayment and Insurance
DBA- Doctor of Business Administration
EAD- Exposure at Defaults
FICO- Fair Isaac Corporation
LR- Logistic Regression
LGD- Loss Given Defaults
LTV – Loan-to-Value
MIG- Mortgage Indemnity Guarantee
MDA- Multivariate Discriminant Analysis
MLE- Maximum Likelihood Estimation
NRB- Nepal Rastra Bank
NPL- Non-Performing Loans
NPV- Net Present Value
NRs- Nepalese Rupees
PARTS- Purpose, Amount, Repayment, Term and Security
PD- Probability of Defaults
USAID- United States Agency for International Development
SMEs- Small and Medium Enterprises

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Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work.

Name: Satish Bhim Narayan Sharma Koirala

Signature:

Date:

Chapter 1: Introduction to Thesis

1.1 Introduction:

At the outset, this Chapter provides the background to the research in which the initial motivation is also discussed. Then, the aims and objectives of the research are presented with an overview of the Nepalese banking sector on which the research is underpinned. The chapter then provides an overview of the thesis, explaining the structure used to move from the theoretical development relating to the research, to the research methods, data analysis and findings and then drawing the conclusions to the research. Further, answers to specific questions such "what is the thesis about", "what has this research found" and "what do these findings mean" are presented.

1.2 Background to the Research:

The South Asian Banking Sector has witness a considerable change in favour of loans and advances during the last 10-15 years. Commercial and Industrial Lending (also known as Corporate Lending) which was the sole source of revenue earnings for the banks and financial institutions has taken a back seat as a result of the economic slowdown, infrastructural constraints and disintermediation (Rao, 2005). Over a period of time, banks have realised that in order to avoid the concentration risk, they need to expand into other lending avenues, which has paved the way for "Consumer or Retail Lending".

From the start of the new millennium, Nepalese banks have started to extend credit to the common man in the form of "Consumer Credit". This has become a new paradigm in the Nepalese banking sector and it includes a comprehensive range of financial services and products such as home loans (mortgages), credit cards, auto loans, educational loans and personal loans. According to the United States Agency for International Development (USAID) report (2000), the urban population in Nepal is expected to grow from 2.6 million to 7.7 million by 2020, which means that this growth would result in investments towards the consumer sector. Subsequently, with the opening of the Nepalese economy to the private sector, there has been a considerable increase in purchasing power and the consumption pattern of the Nepali consumers (The Himalayan Times, 2005).

Consumer credit has enabled the middle class consumer to own a house, a car, a credit card, and also take personal and educational loans (Ramamurthy, 2004). From a growth of about 10 per cent per annum in 2002, consumer credit started accelerating so that growth shot up to 60-70 percent per annum in 2007-2008; constituting about 50 per cent of the total credit portfolio of banks in Nepal (Nepal Rastra Bank, 2008). With the growth in the consumer credit, emphasis is also being placed to develop a prudent credit decision. Within the Nepalese banking sector, the credit decision making is a two way process. Firstly, the credit assistant or the credit supervisor prepares a credit proposal or credit document based upon the applicant's application form and supporting documents. Thereafter, the credit decision is made by the credit officer/manager (based upon his lending authority) who scrutinises the credit proposal using subjective or judgmental evaluation supported by basic financial analysis (Ramamurthy, 2004).

In one of the papers presented to the Forum on Asian Insolvency Reform, Ramamurthy (2004) highlighted that the absence of the consumer risk rating models, risk based pricing methodologies and facility risk rating models were potential drawbacks for an effective consumer credit risk management in Nepalese banks.

Subsequently, in the Annual Bank Supervision Report (2007), Nepal Rastra Bank (NRB), the central bank and regulator of banks and financial institutions in Nepal has emphasised the need for Nepalese banks to adopt prudent risk management systems and the importance for risk based supervision as per the Basel II guidelines. One of the implications for the risk-based approach is that Nepalese banks would have to adopt a risk-based credit decision making framework which would be objective and consistent.

It is against this background leading to the growth of the consumer credit portfolio combined with the need to adopt a risk based credit decision making approach that the author is motivated to explore and address consumer credit risk management, which is an area both under-researched and under-applied within the context of Nepalese banks. Further, the motivation is enhanced as the author has worked for several years in the Nepalese banking sector, in which the thesis is underpinned. Additionally, this thesis has been built upon the work undertaken by the author during the taught component of the DBA programme in which a study was undertaken to investigate the present state of "*credit risk management systems*" in the Nepalese banking sector. The main findings of that study were:

1. Subjective or judgmental method alone was predominantly used across the Nepalese banking sector to assess and evaluate applicants for credit.
2. Banks were aware of the existence of credit risk and were concerned about models and methodologies needed to manage it effectively.
3. Though the non-performing loans (bad loans) were very low in consumer credit areas, no substantiation was found to support that banks were using objective techniques like credit scoring for credit decision making.

Further, the present study would explore the existence and application of consumer credit risk management systems in Nepalese banking sector against the background of the wider use of credit scoring for gaining risk, process and cost-benefits across the consumer credit portfolio. The main outcome of this thesis will be the development of an empirical "Consumer Credit Scoring Model" which could be applied for consumer credit evaluation in the Nepalese banking sector.

In summary, the factors which have contributed to undertaking this research are:

1. The growth of the consumer credit market in Nepal (Ramamurthy, 2004; Upadhyay, 2005; Nepal Rastra Bank, 2004).
2. The sparse literature on consumer credit risk management (MacNeill, 2000; Thomas, 2000; Allen, DeLong and Saunders, 2004; Ramamurthy, 2004)
3. Credit scoring as a credit evaluation method has not been adopted by the Nepalese banks (Ramamurthy, 2004).

1.3 Aims and Objectives of the Research

Up to the time of this research, there are no formal consumer credit decision making models used to evaluate applicants for credit in the Nepalese banking sector. With this background, the researcher aims:

"to study whether the development of an objective credit scoring models is achievable within the Nepalese banking sector".

To address this aim, it is important to study and critically review the current literature relating to the theoretical developments of credit scoring (presented in Chapter 2), which would explain what already exists together with an identification of the issues and questions that have been left unanswered. Further, the research aims to answer the following research sub-questions (also presented in Chapter Three Section 3.3):

1. What is the best method/way to evaluate the creditworthiness of the applicants?
2. What are the factors/characteristics that lenders should consider while assessing an application for consumer credit?
3. What are the issues to be considered while developing and implementing the credit scoring models within new or emerging markets?

Thus, it is expected that the outcomes of this research would help the Nepalese banks move towards an objective, risk based approach for the evaluation of consumer credit and also to adhere to the regulator's guidelines.

1.4 An Overview of the Nepalese banking sector:

In comparison with Nepal's small and underdeveloped economic base, the Nepalese banking and financial system is much diversified with a number of institutions operating in an organised as well as unorganised manner. Until the mid-80s, there were two state-owned commercial banks namely the Nepal Bank Limited (established in 1937 with 51 percent government and 49 percent private shares holding), Rastriya Banijya Bank (established in 1966 with 100 percent government investment) and one state-owned development bank, Agriculture Development Bank (established in 1967 with 100 percent government investment).

In addition, the central banking responsibilities which included the authority to licence, supervise, regulate and develop the banks and financial institutions were discharged by Nepal Rastra Bank established in 26th April, 1956. Its main four functions as enunciated by the Nepal Rastra Bank Act (2002) are as follows:

1. *"To formulate necessary monetary and foreign exchange policies to maintain the stability in price and consolidate the balance of payments for sustainable development of the Nepalese economy",*
2. *"To develop a secure, healthy and efficient system of payments",*
3. *"To make appropriate supervision of the banking and financial system in order to maintain its stability and foster its healthy development, and"*
4. *"To further enhance the public confidence in Nepal's entire banking and financial system".*

Over the last 25 years, the Nepalese banking and financial sector has witnessed a positive shift in terms of its growth and development. As per Nepal Rastra Bank's report (2008) the Gross Domestic Product (GDP) growth rate stands at 5.56 per cent, the financial sector growth rate at 13.81 per cent and the credit growth rate are at 17.50 per cent. This positive move could be attributed to the opening of the banking and financial sector for private investment.

Table 1.1 Nepalese Banks and Financial Institutions:

Type	**Class**	**1980**	**1990**	**2000**	**2008**
Commercial banks	A	2	5	13	25
Development banks	B	1	2	7	58
Finance Company	C	-	-	45	80
Micro-Credit Development banks	D	-	-	7	12
Savings and Credit-cooperatives	Non-classified	-	-	19	16
Non-government organisations (NGOs)	Non-classified	-	-	7	46
Total		3	7	98	237

(Source: Compiled for this research from the Nepal Rastra Bank's website)

Nepal Arab Bank Limited (renamed NABIL Bank Limited in 2002) was established as the first private joint venture bank as a result of the economic liberalisation policy in the mid-80s. Thereafter, other followed and as at 31st October 2008 (presented in Table 1.1), there are 25 class "A" commercial banks, 58 class "B" development banks, 80 class "C" finance companies, 12 class "D" micro-credit development banks, 16 non-classified savings and credit-cooperatives, and 46 non-classified non-government organisations operating in the Nepalese banking sector to deliver the financial products and services (Nepal Rastra Bank, 2008).

In conjunction with the growth in the number of banking and financial institutions, there has also been a significant improvement in the financial highlights as presented in Table 1.2. In mid-July 2008, the total assets/liabilities of the financial system reached to Nepalese Rupees (NRs.) 706324.00 million from NRs. 582477.30 million in mid-July 2007 which shows a growth of 21.26 per cent as compared to the average growth rate of 14.81 per cent for the period 2004-2008.

Table 1.2 Nepalese Banking and Financial Highlights:

(Nepalese Rupees in Millions)

Indicators	**Mid-July 2004**	**Mid-July 2005**	**Mid-July 2006**	**Mid-July 2007**	**Mid-July 2008**
Capital Funds	-1474.30	-9088.10	-7461.47	6901.70	25778.00
Borrowings	13102.90	16217.60	21830.26	26703.67	31391.50
Deposits	258742.30	284115.20	327925.28	391152.60	508905.70
Other liabilities	117061.30	183080.30	163664.30	157719.20	140248.70
Liquid Funds	53448.80	45792.50	47728.06	58064.15	97917.70
Investments	55903.10	55499.10	88959.57	101888.18	120335.60
Loans and Advances	184389.10	209053.70	230424.74	291605.52	391537.70
Other Assets	93691.20	152979.70	138846.08	130919.04	96532.90
Total Assets/Liabilities	387432.20	474325.90	505958.47	582477.30	706324.00

Growth Rates (in %)	**Mid-July 2004**	**Mid-July 2005**	**Mid-July 2006**	**Mid-July 2007**	**Mid-July 2008**	**Annual Average**
Borrowings	12.46	23.77	34.61	22.32	17.55	**22.14**
Deposits	13.12	9.81	15.42	19.28	30.10	**17.55**
Investments	8.64	18.95	33.76	14.53	18.11	**18.80**
Loans and Advances	11.67	13.38	10.22	26.55	34.27	**19.22**
Total Assets and Liabilities	8.50	22.42	6.66	15.12	21.26	**14.81**

(Source: Banking and Financial Statistics, Nepal Rastra Bank, Mid-July 2008, No. 51)

The total deposits, which is a major source of funds for the banking and financial system recorded a growth of 30.10 per cent in mid-July 2008 as compared to the average growth rate of 17.55 per cent for the period 2004-2008. The loans and advances, which form a major component of the assets, also reported a significant growth of 34.27 per cent over the period from mid-July 2007 (NRs 291605.52 million) to mid-July 2008 (NRs 391537.70 million). During the period from 2004-2008, the annual average loans and advances growth rate was recorded at 19.22 per cent (presented in Table 1.2).

Further, according to the Nepal Rastra Bank's Banking and Financial Statistics Report (2008), the 25 'A' class Nepalese commercial banks accounts for a deposit base of NRs 425954.07 million (83.70 percent) and lending of NRs 306574.02 million (78.30 percent) in mid-July 2008 (Nepal Rastra Bank, 2008) which constituted about 71.09 per cent of the credit-deposit ratio (as presented in Table 1.3).

Table 1.3 Soundness Indicators of Class 'A' Nepalese Commercial Banks (in per cent):

Indicators	**Mid-July 2004**	**Mid-July 2005**	**Mid-July 2006**	**Mid-July 2007**	**Mid-July 2008**
Credit/Deposit	59.89	64.86	60.71	68.69	71.09
Capital/Total Deposit	(4.36)	(7.58)	(6.09)	(1.23)	2.34
Capital/Total Credit	(7.29)	(10.82)	(10.03)	(1.79)	3.29
Capital/Total Assets	(3.00)	(4.65)	(4.14)	(4.85)	1.76
Capital Fund /Risk Weighted Assets	(9.07)	(6.33)	(5.30)	(1.71)	4.04
Non-Performing Loan/Total Credit	22.80	18.94	14.22	9.65	6.08
Profitability (NRs in millions)	3707.00	5205.00	7988.51	8797.90	11911.70

(Source: Banking and Financial Statistics, Nepal Rastra Bank, Mid-July2008, No. 51)

In mid-July 2004, the proportion of Non-Performing Loans (NPL) to the total credit of the class 'A' commercial banks stood at 22.8 per cent. However, over the period from 2004 to 2008, the non-performing loans have shown a steady decline to 6.08 per cent in mid-July 2008, which shows a favourable credit climate in the Nepalese banking sector (as presented in Table 1.3).

Table 1.4 Capital Fund/Risk Weighted Assets of Class 'A' Nepalese Commercial Banks:

(in per cent)

Name of the Bank	Mid-July 2004	Mid-July 2005	Mid-July 2006	Mid-July 2007	Mid-July 2008
Nepal Bank Ltd	(24.97)	(19.54)	(29.67)	(32.47)	(22.60)
Rastriya Banijya Bank Ltd	(42.12)	(40.54)	(50.30)	(48.45)	(44.17)
Agriculture Dev. Bank Ltd	*	*	*	4.19	14.93
NABIL Bank Ltd	13.56	12.44	15.08	12.04	11.91
Nepal Investment Bank Ltd	11.18	11.58	12.36	12.17	11.31
SCB Nepal Ltd	15.99	16.36	19.13	15.71	16.80
Himalayan Bank Ltd	10.62	11.10	13.10	12.11	12.50
Nepal SBI Bank Ltd	10.25	9.47	15.01	13.29	12.54
NB Bank Ltd	5.61	3.02	6.70	(23.55)	(16.49)
Everest Bank Ltd	11.07	13.57	12.86	11.19	11.34
Bank of Kathmandu Ltd	11.18	11.22	15.71	12.38	11.47
NCC Bank Ltd	3.42	5.51	5.51	(9.13)	11.22
Lumbini Bank Ltd	8.71	6.35	(13.29)	(7.80)	5.99
NIC Bank Ltd	13.75	13.29	13.62	12.20	12.96
Machhapuchhre Bank Ltd	17.82	11.36	12.98	12.07	11.30
Kumari Bank Ltd	12.81	11.15	12.64	11.20	14.96
Laxmi Bank Ltd	29.13	20.72	14.18	12.43	11.16
Siddhartha Bank Ltd	19.36	13.93	14.83	11.84	11.20
Global Bank Ltd	*	*	*	14.69	11.66
Citizens Bank Intl' Ltd	*	*	*	21.43	11.80
Prime Bank Ltd	*	*	*	*	13.28
Sunrise Bank Ltd	*	*	*	*	14.16
Bank of Asia Nepal Ltd	*	*	*	*	21.30
Dev. Credit Bank Ltd	*	*	*	*	28.23
NMB Bank Ltd	*	*	*	*	36.25
Total	**(9.07)**	**(6.33)**	**(5.30)**	**(1.71)**	**4.04**

*indicates that these were incorporated on the year in which the data is available.

(Source: Banking and Financial Statistics, Nepal Rastra Bank, Mid-July2008, No. 51)

For the safety and soundness of the banking and financial system, one of the major challenges is to maintain the capital adequacy (i.e. the proportion of capital fund to the risk weighted assets) requirements. According to the Nepal Rastra Bank (2007) directives, banks should maintain a minimum capital adequacy ratio of 11 per cent. The average capital adequacy ratio for the class 'A' Nepalese commercial banks stood at 4.04 per cent in mid-July 2008 over the negative structure till mid-July 2007 (as presented Table 1.4). This is mainly due to the large accumulated losses of state-owned Nepal Bank Limited (-22.60 per cent), Rastriya Banijya Bank Limited (-44.17 per cent) and one private sector bank, NB Bank Limited (-16.49 per cent) (as presented in Table 1.4).

The regulatory and supervisory regime of Nepal Rastra Bank is limited to the banks and financial institutions (as presented in Table 1.1) for which it has granted the licence to operate. In this process, Nepal Rastra Bank regularly conducts both off-site and on-site supervision for the safety and soundness of the banking and financial system (Nepal Rastra Bank, 2007). The off-site supervision lays emphasis in validating the financial reports submitted by the banks and financial institutions. If any discrepancies are found in the off-site supervision, then an on-site supervision is carried out. This form of supervision has some limitations as it is labour intensive and transaction oriented, in which the focus is on detecting minor mistakes rather than the overall risk management aspect of the banks (Nepal Rastra Bank, 2007). However, the on-site supervision is uniformly applied to all class 'A' Nepalese commercial banks, which is based upon the CAMELS/CAELS approach (Basel Committee on Banking Supervision, 1988) where capital adequacy, asset quality, management aspects, earnings, liquidity and sensitivity to market risk are examined (Nepal Rastra Bank, 2007).

In recent years, with the globalisation and consolidation of the financial system all over the world, one of the major challenges for regulators and supervisors is to maintain stability of the banking and financial system. In this process, the Bank of International Settlements (BIS) has stressed the need to adopt a comprehensive risk-based supervision approach through the adoption of the Basel II Accord from January 2008 onwards (Basel Committee Banking Supervision, 2004). The Basel II Accord is aimed at building a solid foundation for capital regulation, supervision and market discipline thereby enhancing the financial stability and risk management systems in banks and financial institutions all over the world (Basel Committee Banking Supervision, 2004). In the risk-based approach, supervisors would go through the systems and procedures placed by the banks and financial institutions for managing and controlling the inherent risks.

In new and emerging economies such as Nepal, there is no pressure to adopt the Basel II Accord guidelines by the deadline that has been set of adoption with effect from January 2008 onwards. However, Nepal Rastra Bank (2007) in its banking supervision policy document had decided to make preparation to move forward with the risk-based supervision with the implementation of the Basel II Accord in a simplified form (simplified standardised approach for credit risk; basic indicator approach for operational risk and net open exchange model for market risk). In preparing for this risk-based supervision approach under the Basel II Accord guidelines, Nepal Rastra Bank have instructed all class 'A' Nepalese commercial banks: "*to adopt a risk focussed internal audit system; to strengthen the management information system and information technology; to set up dedicated risk management teams at the corporate level; to reorient the internal audit department by undertaking risk-based audit; and finally to set up a compliance unit which would ensure that complete compliance is made within the time period as stated by the regulator*" (Nepal Rastra Bank, 2007).

The transition from the traditional to the risk-based approach based on the Basel II Accord guidelines would be challenging both for Nepal Rastra Bank as well as the class 'A' Nepalese commercial banks with respect to the availability of the resources, the effectiveness of the internal control systems, corporate governance and the risk management practices adopted. One of the implications of the risk-based approach is that Nepalese banks have to adopt a more sophisticated risk based credit decision framework which is objective, consistent and could achieve improved risk management. In this process, this research intends to evaluate the present consumer credit decision system operating in the Nepalese banking sector, with an objective to offer an alternative risk based consumer credit decision making technique known as credit scoring, so that Nepalese banks could adopt similar technique to enhance its credit decision making process and risk management systems.

1.5 Structure of the Thesis:

The thesis is presented in six chapters. The first part of the thesis contains Chapters One, Two and Three that address the question 'what is the thesis about?' The second part of this thesis relates to the analysis and findings (presented in Chapter Four) and answers the question 'what has this research found?' and the final part of the thesis relates to conclusions, contributions and research implications (presented in Chapter Five) which addresses the question 'what do these findings mean?'.

1.5.1 What is this thesis about?

The first three Chapters of this thesis establish the background to the research. Chapter One describes the background to the research, the researcher's motivation and interest (presented in Section 1.2). This is followed by the aims and objectives (presented in Section 1.3) of the research which justifies why the research is important in respect of both the theory and practice. Thereafter, an overview of the Nepalese banking sector (presented in Section 1.4) on which this research is based is presented.

Chapter Two relates to the theoretical development relating to credit scoring in the consumer credit which sets up the foundation on which this research is based and also builds the conceptual framework in the area of home loans. This chapter provides the discussions of the findings of other researchers, thereby identifying the gaps in the literature, which helps to develop the research questions.

Chapter Three describes the research methods applied in this research. Discussion is rooted on the appropriate philosophical paradigm adopted for this research. Thereafter, the mixed methods research design in terms data collection process and its method of analysis are presented in three sections. Section one relates to the preliminary study questionnaires, in which the questionnaire design, sampling choice, its administration and method of analysis (exploratory factor analysis) are presented. The second section relates to the expert interviews, in which the development of the expert interview guide, the piloting process, the sampling choice, its administration and method of analysis (matrix analysis) are presented. Thereafter, in the final section the credit application forms data collection process, its sampling choice and method of analysis (logistic regression) to develop the credit scoring model are presented. This is followed by a discussion on the validity and reliability of the mixed methods research approach. Finally, this chapter ends with the discussion of the strengths and limitations of the mixed methods research approach supplemented by the ethical considerations which have been adhered to in this research.

1.5.2 What has this research found?

Chapter Four relates to the analysis and discussion of findings in which the outcome of the analysis are discussed with reference to the earlier research in the area of credit scoring presented in Chapter Two and as well as in the context of answering the specific research question and sub-questions.

1.5.3 What do these findings mean?

In Chapter Five conclusions are drawn by discussing the research questions, highlighting the limitations of the research and making recommendations for future research. Finally, the contributions and implications this research has made in terms of professional development and practice and the researcher's personal reflections on the research are presented.

1.6 Chapter Summary:

This introductory chapter has laid the foundation for the thesis. The background to the research and also the initial motivation has been justified. The aims and objectives of this research with an overview of the Nepalese banking sector have been outlined. Finally, the overview and structure of the thesis are presented.

Chapter 2: Credit Scoring in the Consumer Credit Decisions

2.1 Introduction:

It is imperative for banks and financial institutions to evaluate and assess the creditworthiness of the applicant before granting credit. In the early 1990's, one of the authorities in credit scoring, Lewis (1992), notes that when credit was granted only to a few known applicants, the credit decision making process was based on the subjective or judgmental evaluation of the applicants, which was thought to be appropriate for that period. However, in recent times there has been a significant growth in the consumer credit industry (Hand, 1998) with banks and financial institutions offering an array of financial products and services to a larger and varied consumer market (Anderson, 2007).

In order to cope with the changing market environment, statistical techniques such as credit scoring have been tried and tested by lenders in the developed markets such as the UK and US. Credit scoring has been developed to provide an objective, fast, cost-effective and risk based approach to evaluate the application for credit (Lewis, 1992; Thomas, 2000; Mays, 2004). On the same note, evidence from the emerging markets such as Brazil, Russia, India and China also points to the increased use of credit scoring by lenders, with the most significant growth being during the period after 2000 when the volume of consumer credit expanded significantly (de Andrade and Thomas, 2007; Kordichev and Katilova, 2007; Rao, 2005; Thanh and Kleimier, 2006). However, in new markets like Nepal, though consumer credit emerged in the early 2000, the use of credit scoring is still very much at a nascent stage (Ramamurthy, 2004; Upadhyay, 2005). This being the case, with limited or no application to date there is justification for looking at the development and use of a credit scoring model that could complement or replace the present system of consumer credit decision making.

In order to elucidate the research questions and build up a theoretical framework for the study, this chapter provides a review of the development relating to credit scoring. The chapter starts with an overview of the consumer credit industry, the importance of consumer credit and the inherent risk it bears. Thereafter, a brief review of the credit decision making process is presented with a justification for the adoption of an objective approach. Following this justification, the author provides different perspectives on credit scoring, its types, methods, benefits and limitations. Furthermore, the determinants of the predictive power of the credit scoring model are discussed before describing the different credit scoring models. Building upon the above discussions, the credit scoring modelling issues in terms of model overrides, model validation and performance are discussed. Thus, the chapter concludes by building the conceptual framework underpinning this research which is based on home loans. Overall, this chapter aims to review the relevant concepts and theories of credit scoring so as to support further analysis and discussion.

2.2 The Consumer Credit Industry:

Financial Institutions, especially banks, exist in order to provide "credit" to the ultimate borrower which may be businesses or individuals. In this context, credit means lending a principal amount now with the anticipation of receiving the principal along with interest at a future date. The word "*credit*" is derived from the Latin word "*credo*" which means "trust in" or "rely on" (Anderson, 2007, p.3). That is when the bank lends; it has to "trust in" or "rely on" the individuals or businesses to honour the obligation. When such credit applies to individual it is referred as "*consumer credit*" or "*instalment credit*" (Danielian, 1929, p.394).

According to Lewis (1992, p. 16), "*consumer credit has been around for 3000 years since the time of Babylonians*". While *"For the last 750 years of that time there has been an industry in lending to consumers beginning with the pawn brokers and the usurers of the middle ages, but the lending to the mass market of consumers is a phenomenon of the last 50 years"* (Thomas, Oliver and Hand, 2005, p.2). Consumer credit has come of age from the early finance houses established in the 1920s (that is, GE Capital and GM Finance) (Lewis, 1992), to the arrival of the credit cards in the 1960s and was later matched by the growth in credit offered by other consumer products such as mortgages, personal loans, overdrafts, auto loans, education loans, travel loans (Chandler and Coffman, 1979; Thomas *et al.*, 2005, Bhatia, 2006).

According to the United Kingdom Consumer Credit Act 1974, "*Consumer Credit*" is defined as the borrowing by individuals to finance current expenditure on goods and services. Consistent with this definition, Hand (1998, p.69) describes "*Consumer Credit as the supply of goods or services to be paid for by an individual at some future time or times along with interest*". While Bhatia (2006, p. 66) puts *"Consumer Credit as a homogeneous portfolio comprising a large number of small, low-value loans to individuals and where the incremental risk of any single exposure is small"*.

Further, Jacobson and Roszbach (2003) emphasised the role which consumer credit plays in terms of being an important instrument in the financial planning of households as well as an asset on the balance sheet of lenders. Thus, consumer credit has become an industry in its own right (Lewis, 1992; Hand and Henley, 1997; Thomas, 2000) with the total consumer credit outstanding in the United States estimated at US$2,420 billion[1] (December 2008) and in the United Kingdom estimated at £212.85 billion[2] (December 2008). The significant growth in the consumer credit industry is being attributed to the plethora of credit products being offered through channels such as the supermarket chains and retailers (Hand, 1998; Anderson, 2007). This has been facilitated by the rapid growth in the number of databases holding details of consumer information and by their combination (debit and credit card usage, savings and current account usage, mortgages) into a single entity by credit bureaus like Experian. This has made its significantly easier for the lenders to offer more products and services on a regular basis to both existing and potentially new clients.

Banks and financial institutions channel their deposits by creating an array of credit products and extending them to the consumers and businesses, thereby generating profits. While extending the credit, the initial credit assessment and evaluation process is of paramount importance. Banks which are overly restrictive may ensure minimal loss, but they are unlikely to result in maximum profits because of the opportunity cost of loans rejection which may exceed potential bad debts costs. Conversely, the credit policies and practices which are liberal may result in bad debt losses, which unduly reduce the banks' profits. Therefore, it could be argued that it is not the resolution of credit losses, but the cause of such losses that should be addressed.

Further, the work of Apilado et al., (1974) supports the above argument by indicating that the judicious evaluation of credit applications is obviously crucial in achieving an appropriate trade-off between profitability and risk. Thus, in view of the growing

[1] Data from the Federal Reserve Board, Assets and Liabilities of Commercial Banks in the US
[2] Data from www.statistics.gov.uk

and significant role of consumer credit within the financial sector, the credit assessment process has assumed increasing importance both to the consumer in terms of fair assessment and more importantly the lender to trade-off risk and profitability (Chandler and Coffman, 1979; Lewis, 1992; Hand, 1998; Thomas, 2000; Anderson, 2007).

"If the principal on all financial claims held by the banks was paid in full on maturity and interest payments were made on the promised dates, banks would always receive back the original principal lent plus an interest return" (Saunders and Cornett, 2006, p. 287). That is, they would face no credit risk. If a borrower defaults, however, both the principal loaned and the interest payments expected to be received are at risk. It is this risk, due to uncertainty in consumer's ability to meet their obligations, which is known as Consumer Credit Risk (Thomas, 2000; Bessis, 2002; Heffernan, 2005; Bhatia, 2006; Hull, 2007). *"Credit risk arises because of the possibility that promised cash flows on financial claims held by banks on loans will not be paid in full"* (Saunders and Cornett, 2006, p. 287).

Myers and Forgy (1963) have cited that the problem of determining credit risk has been with the lender, since he first consummated a business transaction without receiving immediate payments for his goods and services. It is interesting to note that even 45 years later, the problem of managing credit risk continues to consume the lender. Lenders still struggle to find the most efficient and accurate method of measuring and managing credit risk. Further, it could be argued that an approach that is legal, economically viable, timely and perceived by customers and intermediaries as being fair is essential in order to assist the credit decision making process (MacNeill, 2000).

However, while undertaking the credit decision making process lenders are faced with six functional responsibilities, such as risk assessment, adherence to credit guidelines, loan monitoring, receivables collection, loan loss provisioning and financing the investment in receivables (Summer and Wilson, 2000). Risk assessment which includes the processing, analysis and classification of the applicant for credit constitutes the most vital element in the bank's credit risk management system. A judicious credit assessment and valuation system is also important to the borrower, as this would signify that credit would be available on a fair basis. Thereby, both the lender and the borrower benefits from an effective and efficient credit evaluation system that allows the widest availability of credit while reducing operating expenses and minimising bad debt losses (Chandler and Coffman, 1979).

2.3 Judgmental Lending and Consumer Credit:

Traditional methods of deciding whether to grant credit to a particular individual use human judgment to evaluate the creditworthiness of the applicant, drawing from the experience of previous lending decisions. The end result of the evaluation process is to provide a 'measure of creditworthiness' (Lewis, 1992; Thomas, 2000; MacNeill, 2004; Sidiqqi, 2005). According to Lewis (1992, p.3), *"Creditworthiness is a characteristic of an individual that makes him or her, a suitable candidate for the extension of credit while someone who is not creditworthy is, conversely, unsuited to credit"*. Thus, creditworthiness implies an applicant's ability and willingness to repay the loan obligation as per the agreed terms and conditions.

Credit officers examine the credit applicant's characteristics, evaluate the applicant's creditworthiness and decide to approve or to decline the applicant (Chandler and Coffman, 1979). If the lenders find that the applicant's creditworthiness is not satisfactory then they would either increase interest rates charged to offset the extra risk or put extra effort into determining what information can add value, and how to obtain and assess it (Chandler and Coffman, 1979; Stanton, 1999).

As pointed by Hand (1998), in the subjective approach the decision as to whether or not to grant credit is based on the experience and personal knowledge of the credit officers. The subjective approach may also incorporate rules and other non-empirically derived credit guides established by the institution's policies (Chandler and Coffman, 1979). The subjective credit granting decision may also be driven by what is referred to variously as the 3Cs, the 4Cs or the 5Cs of consumer credit (Thomas, 2000) as presented in Table 2.1:

Table 2.1: Cs of Consumer Credit

Cs	Implication
Character	The character of the applicant signifies whether the applicant or his family is known to the lender.
Capital	The amount of credit or loan the applicant is applying for.
Collateral	Collateral represents the applicant's equity or security for the loan. For home loans, the property forms the collateral for the loan.
Capacity	This is the applicant surplus income
Condition	This is the macroeconomic market conditions, such as interest rates, inflation, economic conditions.

(Source: Thomas (2000) A survey of credit and behavioural scoring: forecasting financial risk of lending to customers, *International Journal of Forecasting*, Vol. 16, pp. 149-172)

Apart from the above Cs, the credit decisions of the lenders were guided by other credit industry wide acronyms such as The Canons of Lending- CAMPARI (as presented in Table 2.2) and PARTS (as presented in Table 2.3).

Table 2.2 The Canons of Lending-CAMPARI

CAMPARI	Implication
C	Character – of the applicant?
A	Ability – to pay off the loan? The applicant source of income.
M	Margin – what is the applicant's contribution to the total project?
P	Purpose – Is the loan in accordance with the banking policy or against it? Is it illegal or is the bank cautious of the market sector?
A	Amount – Is the amount being asked for appropriate?
R	Repayment – the mode of repayment of the loan has to be established before the loan has been disbursed?
I	Insurance- adequate collateral security should be established against the loan, in case of the loan default, the lender can easily realise the amount.

(Source: Various)

Table 2.3 PARTS

PARTS	Implication
P	Purpose- of the loan; is the loan purpose acceptable?
A	Amount- of the loan; how much does the customer requires, and is that all the customer requires?
R	Repayment of the loan; does the customer have sufficient income to cover the repayments?
T	Term of the loan; over what timeframe will the loan be repaid?
S	Security of the loan; does the loan require a collateral as security?

(Source: Various)

Given the prevalence of the "human element" i.e. experience, judgment and common sense, supported by some basic numerical support in credit decisions (Banks, 2002); central to the granting of credit, is the estimation of risk- in terms of identifying good and bad credit risks (Lewis, 1992). It is important to evaluate the credit based on the two questions: what is the risk presented by the applicant and what is the maximum risk that the lender should accept (Lewis, 1992). The development of sophisticated mathematical and statistical modelling techniques has not led to the total demise of the subjective framework to grant credit. However, Anderson (2007) points out that the subjective evaluation is still used in the case of relationship lending, or any lending where little data or experience exists.

Within the credit scoring literature (Capon, 1982; Lewis, 1992; Hand, 1998), the importance of subjective evaluation has been criticised due to some inherent shortcomings. The main shortcomings of the subjective framework are credit officer errors, inconsistency in application of credit policies between credit officers, high costs both in training and employing credit officers, a slow credit decision making process and lack of quantification of the credit risk.

However, Bunn and Wright (1991) have advocated that the subjective approach can be beneficial in a lending environment which has little or only unstructured data. They can also be applied to emerging retail markets, where the rules are not well defined, especially Small and Medium Enterprises (SMEs) and high net worth individuals, corporate lending, where the data is minimal, but the margins are sufficient for the risk undertaken (Anderson, 2007). Consequently, with the rapid growth in the consumer credit industry, lenders have been advocating the need for an objective, fast, reliable and consistent credit decision making framework to replace or complement the subjective system (Lewis, 1992; Hand and Henley, 1997; Hand, 1998; Thomas, 2000; Bhatia, 2006; Anderson, 2007). Such objective approaches have been developing over a number of years and are discussed in the next section.

2.4 The Advent of an Objective Approach:

It was Durand (1941) who developed the first credit scoring system, using discriminant analysis, for the United States National Bureau of Economic Research to investigate instalment loans made by 37 firms, which showed that the method could produce good predictors of credit repayment (Hand and Henley, 1997). The widespread diffusion of the statistical methods did not occur until development of the necessary computer technology in the early 1960s (Capon, 1982). This supplemented by economic pressures facilitated the development of an objective credit decision framework known as Credit-Scoring (Capon, 1982; Lewis, 1992; Thomas, 2000).

According to Reichert *et al.,* (1983), the dramatic growth in consumer lending coupled with the increasing concern regarding discriminatory lending practices has generated considerable interest on the part of the lenders in developing objective statistically based credit scoring models. Thomas (2000) reports that on average individuals in the United Kingdom and the United States are credit scored at least once a week. However, Reichert *et al.,* (1983) emphasised that the objective techniques, employed singly or in combination, can be useful in understanding the basics of the credit-granting process, while human subjective judgment and past experiences of the credit officers on the loan performance are necessary when used in conjunction with the objective techniques for a more complete analysis. The real benefit of the statistical approach to credit decision making usually relate to it being highly objective, efficient and consistent (Lewis, 1992; Thomas, 2000; Bhatia, 2006; Anderson, 2007). However, it could be argued that in markets which are not developed and for markets containing a small number of customers, the cost associated with such sophisticated systems might be too high when compared against the benefit derived from using the system. Thus, in the Nepalese banking sector with the growth of consumer credit, the need to adopt such an approach is inevitable in the future.

Mays (2004) argue that the costs and benefits derived out of the objective system have placed high pressure to limit subjective evaluation of the credit applications. However, Anderson (2007) advocates that subjective evaluation should be used in situations such as high valued credit where scoring systems cannot capture applicants' information and the potential profits from such lending are high. In the Nepalese banking sector, the consumer credit granting decision is currently based upon the subjective or judgmental criteria discussed earlier, using the industry wide acronyms presented in Tables 2.1-2.3 supplemented by some basic financial analysis (Ramamurthy, 2004; Nepal Rastra Bank, 2008). However, with the growth in the consumer credit portfolio, reflecting global banking developments and the increased emphasis placed on risk management practices by the banks and the regulators (Nepal Rastra Bank, 2008), there is a need to devise an objective evaluation framework to support the current consumer credit decision making process. It is this which will be considered within the empirical research presented in this thesis.

2.5 Challenges to the Use of Credit Scoring:

In simple terms, credit scoring means transforming relevant data into numerical measures to guide credit decisions (Lewis, 1992; Anderson, 2007). It is also associated with the need for an objective, fast and consistent assessment of the risk associated with credit decisions (Lewis, 1992; Thomas *et.al.,* 2002; Bhatia, 2006, Siddiqi, 2005; Crook *et al.,* 2007). *"Credit Scoring is a statistical method used to predict the probability that a loan applicant or existing borrower will default or become delinquent"* (Mester, 1997, p. 3). According to Bhatia (2006) the meaning of "credit scoring" is to assign scores to the characteristics of debt, borrowers, historical default and other loss experienced as an indication of the risk level of the borrower. It aims to estimate the risk of the client in their loans, but not explain it (Thomas *et al.,* 2002; Mays, 2004); this is considered important because the lender could classify applicants according to the inherent risk it bears. Hsia (1978) defines *"Credit scoring as an empirical technique that uses statistical methodology to predict the* *probability of repayment by credit applicants".* It uses statistical tools to transform the applicant information to obtain an overall credit risk index or score for an applicant.

Basically, credit scoring is a method which can be used to classify or quantify the risk factors relevant for a borrower's ability and willingness to repay the loan. Credit scoring allows lenders to predict likely loan outcomes based on the use of statistical techniques, which allow objective predictions as to whether a loan will produce a good or bad outcome (MacNeill, 2000). Credit scoring can be used on a standalone basis or as a part of the credit evaluation process. When used on a standalone basis, credit scoring assists in classifying applicants into accept/reject groups or good/bad credits; when used as part of the credit evaluation process, credit scoring can help to measure the credit risk of the applicants (Thomas *et al.,* 2002; Bhatia, 2006). This idea of discriminating between groups in a population was introduced in statistics by Fisher (1936).

As already noted Durand (1941) was the first to recognise that one could use the same techniques to discriminate between good and bad loans. *"Credit scoring is essentially a way of recognising the different groups in a population when one cannot see the characteristic that separates the groups"* (Thomas, 2000, p.151). Commercially, credit scoring was first developed in the 1950s by Bill Fair and Earl Isaac, but has only come into increasing use in the last two decades (Thomas, 2000). The main aim of the credit scoring model is to build a single aggregate risk indicator for a set of risk factors from analysis of data representative of the lender's own previous lending experience (Thomas, 2000; MacNeill, 2000; Bhatia, 2006).

Further, Crook *et al.,* (2007, p. 1447) emphasised that *"consumer credit risk assessment involves the use of risk assessment tools to manage a borrower's account from the time of pre-screening a potential application through to the management of the account during its life and possible write-off".* Credit scoring could be used in decision processes, wherein lenders define different scenarios using scores and policy, and then identify action to be taken in each case, such as accept or reject the credit application, set maximum or minimum limits on the loan value or repayment amount, calculate interest rate charges and determine the period of the loan term granted (Mays, 2004; Anderson, 2007). Within the consumer credit industry, credit scoring has been widely used in the areas of unsecured and secured lending, store credit, service provision and enterprise lending as is summarised in Table 2.4.

Table 2.4 Uses of Credit Scoring

Types of Lending	**Product/Market**
Unsecured	Credit Cards, Personal Loans, Overdrafts.
Secured	Home Loan Mortgages, Vehicle Finance.
Store Credit	Clothing, Furniture, Mail Order.
Service Provision	Phone Contracts, Municipal Accounts, Short-Term Insurance
Enterprise-Lending	Working Capital Loans, Trade Credit.

(Source: Adapted from Anderson (2007) The Credit Scoring Toolkit)

2.5.1 Types of Credit Scores:

According to Asch (1995), a credit score is assigned to an applicant based upon the credit classification or risk assessment. Whichever types of scores are being used, the main concern for the lender is the estimation of the probability of default. Perhaps the greatest benefit the credit scoring system can provide is in the realm of risk assessment (Crook *et al.,* 2007; Anderson, 2007). Within the credit scoring literature, authors (Thomas, 2000; Mays, 2004; Bhatia, 2006; Anderson, 2007) have indicated different types of credit scores that the banks may formulate in assisting the credit decision process. These credit scores are differentiated according to its applicability as well as its stage of development, which has been summarised in Table 2.5.

Table 2.5 Types of Credit Scores:

Credit Scores	Description
Application Score	*It is used to make decisions on new credit applications.* Application scoring models are the credit risk or default predictive models. They are designed to classify applicants into good or bad credit risk. Thus, the lender is able to categorise between those applicants whom the lender is confident will repay a loan or card or manage their account properly and those applicants about whom the lender is insufficiently confident.
Behavioural Score	*It is used to supervise the existing credit.* If the existing customer wants to increase his/her credit limit should the bank agree to that? What marketing if any should the bank aim at that customer? If the customer starts to fall behind in his/her repayments what actions should the bank take? These scores can be used to help the credit decision making process by forecasting future performance of the customer.
Collections Score	*It is used as part of the collection process.* Lenders usually use this score to distinguish customers who have missed payments and are on the delinquency list. An array of behavioural, bureau and collections data are used to generate this score.
Bureau Score	*It is developed by the credit bureau based upon the data held by them.* Some of the well know bureau score are: FICO score- a general default risk score developed by Fair Isaac Corporation; DELPHI score- bankruptcy score developed by Experian; BEACON-FICO score- credit score developed by Equifax.

(Source: Various)

The credit scores are used by the lenders to predict delinquencies, to make credit decisions, and more recently to derive probability of default (PD), exposure at default (EAD) and loss given default (LGD) estimates required by the Basel II Accord (Basel Committee Banking Supervision, 2004). The credit decision is taken by comparing the estimated probability of default generated by the scoring system with a suitable threshold limit set according to the risk appetite of the lender. The data source for developing the credit scoring model is obtained through the customer credit application forms, financial and bank statements, past customer credit history, credit bureau data and country court judgments data (Lewis, 1992; Mays, 2004). Reflecting the established position of the subjective approach it is perhaps not surprising that credit scoring uses very similar information and criteria, the value-added of this approach coming from the greater degree of objectivity and consistency.

2.5.2 Credit Scoring Methods:

According to the way in which the credit scores are obtained, credit scoring methods can be divided into: (i) *"Deductive or Judgmental Credit Scoring"* and (ii) *"Empirical or Statistical Credit Scoring"* (Muller, 1997; Liu, 2001; Caire, 2004):

2.5.2.1 Deductive or Judgmental Credit Scoring:

The deductive or judgmental credit scoring system awards points (weights) to the particular attributes of the credit applicant in accordance with the lenders' credit policies and risk management preferences. The weighted values of the attributes are aggregated to a total score. A typical deductive or judgmental credit scoring model could be built up following the steps as given by Caire (2004):

Step 1: Selecting the Creditworthiness Factors: These are the factors which the credit officer would consider in evaluating the creditworthiness of the applicants (presented in Table 2.6). They stem from the bank's minimum lending criteria for the credit product such as, for example for home loans.

Table 2.6 Example of Creditworthiness Factors

Lending Criteria/Variables	Acceptable Value
Age of the applicant	Should not exceed 60 yrs
Salary (Income)	Double of the monthly instalment
Type of Service (Occupation)	Permanent
Margin Money (Deposits)	Minimum 25%
Period of loan (term)	Maximum 20yrs

(Source: Illustrative example developed for this research based on professional experience of the researcher)

Step 2: Weighting the Creditworthiness Factors: Based upon the above minimum lending criteria, Banks could assign scores to these factors from a range of 0 to 1; or 0, 10, 20, 30; or according to the banks' credit policy (presented in Table 2.7).

Table 2.7 Sample Scorecards based on Deductive or Judgmental Credit Scoring:

Sample Scorecard 1

Variable/Factors	Score Assigned
Age	>60 = 0 <60 = 1
Salary	<2 times instalment = 0 >2 times instalment = 1
Type of Service (Occupation)	Temporary = 0 Permanent = 1
Margin Money	<25% = 0 >25% = 1
Period of Loan	>20 yrs = 0 <20 yrs = 1

Sample Scorecard 2

Variable/Factors	Score Assigned
Age	18-25 = 10 25-40 = 30 40-60 = 20 >60 =0
Salary	<2 times instalment = 0 >2 times instalment = 10 >5 times instalment = 20 >10times instalment =30
Type of Service (Occupation)	Temporary = 0 Permanent = 10
Margin Money	<25% = 0 >35% = 10 >45% = 20 >50% = 30
Period of Loan	0-7yrs = 10 7-15yrs = 20 15-20yrs =30 >20yrs=0

(Source: Illustrative example developed for this research based on professional experience of the researcher)

The sample scorecard 1 (presented in Table 2.7) gives equal weighting/score to the lending criteria/variables. For example, an applicant qualifying for the loan should have scored 3 out of 5 to pass the model or whatever level has been set as per the credit policy of the lender. However, in sample scorecard 2 (presented in Table 2.7), the lending criteria/variables are expanded and different weighting/score in the range of 0,10,20,30 are assigned. Based upon the total score obtained by the applicant by the application of scorecard 2, the lender makes a credit decision as per its credit policy, which might be illustrated in Table 2.8.

Table 2.8 Credit decision based on the total score obtained

Total Score Obtained	**Credit Decision**
Less than 50	Reject the Loan
50-80	Ask for more information
Above 80	Grant the Loan

(Source: Illustrative example developed for this research based on professional experience of the researcher)

In a new market segment, where historical data on the customer is limited or non-existent, lenders may use the deductive or judgmental credit scoring method. Although, this technique enables the lenders to classify the applicants according to the scores obtained, it must be noted that the scores are based on the subjective criterion of the lender, and as a result it can be argued that they lose effectiveness, consistency and objectivity. Thus, the inherent shortcomings of the deductive or judgmental credit scoring system as summarised by Keyzlar and Wagner (1996) are that the lending characteristics are analysed sequentially rather than in combination thereby ignoring their correlation, it also fails to capture the risk trade-offs that the lenders are usually willing to make. And finally, the score assigned to the characteristics or variables are based upon the subjective framework as decided by the lenders and does not reflect the inherent risk the characteristics would bear.

2.5.2.2 Empirical or Statistical Credit Scoring:

The empirical or statistical credit scoring models are commonly structured along the lines of Altman's (1968) "Z-score model" which used multivariate discriminant analysis (MDA) and has been applied to predict commercial firms' bankruptcy. Altman (1968) used the discriminant function on commercial firms' historical data to obtain the Z-score using five financial ratios: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market capitalisation to book value of debt and sales to total assets.

In choosing these ratios for use within the discriminant function, Altman (1968) examined the statistical significance of various alternative functions, interrelationship between the relevant variables and the predictive accuracy of various characteristics and produced the Z-score model, which is given as Equation 2.1. This model was established using historical firms data. Once the Z-score is calculated it is compared against a criteria formulated to predict the probability of failure of the firms known as the Z-score criteria (presented in Table 2.9). Thus, whether a firm would be bankrupt or not could be established using the Z-score obtained against the benchmark presented in Table 2.9.

$$\mathbf{Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5} \qquad \textbf{(Equation 2.1)}$$

Where, X1 = working capital/total assets,
X2 = retained earnings/total assets,
X3 = earnings before interest and taxes/total assets,
X4 = market capitalisation/book value of debt,
X5 = sales/total assets, and
Z = overall index.

Table 2.9 Z-score criteria

If the Z-score is	Then the probability of failure of the firms is
Less than 1.8	Very High
Between 1.81 to 2.99	Not Sure
Greater than 3.0	Unlikely

(Source: Altman (1968) Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy)

Working on the impetus from the Altman's 'Z-score' model, empirical or statistical credit scoring models for consumer credit decision processes are built using historical customer data internal to the bank combined with suitable statistical techniques (Lewis, 1992; Hand and Henley, 1997; Thomas, 2000; Liu, 2001; Bhatia, 2006; Crook *et al.,* 2007). One of the major problems made here is the assumption that new loan customers replicate past customers and on that basis the credit-scoring system can be used to calculate a credit score for new applicants and assign them to a "good" or "bad" group (Saunders and Cornett, 2006). Naturally, this assumption might fail to hold under extreme macroeconomic or changing market conditions.

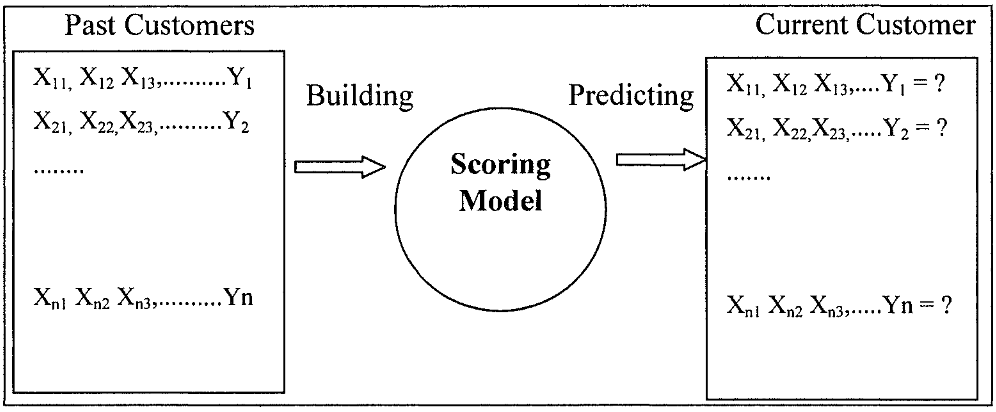
The overall aim of the credit scoring developed from the early Z-scores is to obtain a predictive model which could rank cases by their probability of being good or bad at a future date, based upon the past experiences of the lender. The basic principle in credit scoring is that by selecting and combining different financial and economic characteristics of the applicant, the lender may be able to separate good and bad customers based on a single numerical value (similar to the Z- score) rather than as a judgmental assessment of several separate characteristics (Saunders and Cornett, 2006). This approach enables the lender to evaluate the creditworthiness of the applicant quickly, consistently thereby increasing the transparency of the credit decision process.

In addition, the lenders could not have expanded their credit portfolios to the same extent, without using an accurate and automated risk management tool as the time taken in judgmental credit decision were long and not consistent (Lewis, 1992; Thomas *et al.,* 2002; Siddiqi, 2005). The basic empirical credit scoring process (presented in Figure 2.1) essentially involves two steps (Lewis, 1992; Liu, 2001; Bhatia, 2006) :

1. ***Model Building:*** In a first step, it uses historical customers' data from the credit files such as age, income, occupation combined with an appropriate statistical technique in order to identify which borrower characteristics are best able to distinguish between good and bad risks.

2. ***Model Prediction:*** In a second step, the model is used to calculate a score for each new loan applicant.

Figure 2.1: The Process of Credit Scoring



(Source: Adapted from Liu, (2001) New Issues in Credit Scoring Application)

As illustrated in the Figure 2.1, the input data is historical data on '*n*' credit customers with a known set of risk characteristics. The input data is in the following format. Independent characteristics or variables : X_{ij} , i= 1,......,n customers, j = 1,... r risk characteristics and Dependent characteristic or variable: Y_i, i= 1,....n. Where, X_{ij} is the value of the j^{th} characteristics of the i^{th} customer and Y_i is the known risk characteristics of the i^{th} customer. The risk values can either have two values (e.g., default or non-default) or have multiple values (e.g., different classes of risk levels). The scoring model is generated from the input data through statistical techniques and is applied to current customers to predict their unknown value of the dependent characteristic or variable 'Y'.

A credit decision is taken based on this prediction of 'Y'. The prediction can either be the risk class with two or multiple categorical values or a continuous score (from 0% to 100%, which may for example, be representing the default probabilities). If 'Y' can be taken from a stream of continuous values, a credit decision is made by comparing the value of 'Y' with a suitable threshold set according to the lenders' credit policy. Thus, the credit scoring model aims to find out the value of the unknown credit risk indicator given the values of the independent credit risk characteristics for a current customer. The issues relating to the model performance and validation are discussed in section 2.9.2.

2.6 Benefits and Limitations of Credit Scoring:

Credit scoring has been a powerful tool to aid the consumer decision making process in the consumer market shift from relationship lending to transactional lending. Lenders are using credit scoring mainly for application screening, but it is also being used in account management, collections and recoveries, fraud, risk pricing and marketing. The benefits that could be derived from credit scoring are summarised in

Table 2.10 (Churchill, Nevin, and Watson, 1977; Mester, 1997; Stanton, 1999; MacNeill, 2000; Bhatia, 2006; Anderson, 2007):

Table 2.10: Benefits of Credit Scoring:

Benefits Derived	Descriptions
Predictive Accuracy	Credit scoring takes into consideration the correlation among the characteristics and provides a measure which provides the most accurate prediction of the credit performance. So that credit decision making is improved.
Time Savings	Credit scoring greatly reduces the time taken and in the credit approval process. A study by Allen (1995) reported that by using credit scoring the loan approval process averages about 12 hours per small business loan which in the past would have taken up to two weeks to process.
Cost Savings	The time savings provide cost savings for the banks which means benefits to the customer as well. Customers need to provide only the information used in the scoring process, so applications could be shorter. Thus credit scoring reduces the loan processing costs.
Objectivity	Another benefit of credit scoring is that it improves objectivity which minimises human bias in the credit decision making process. This objectivity helps the lenders ensure that they apply the same assessment criteria to all applicants regardless of colour, gender, race or other factors prohibited by law from being used. Further, the credit scoring model also makes it easier for the lender to justify the business reason for using a characteristic that might have a disproportionately negative effect on certain groups of applicants protected by law from discrimination.
Consistency	Credit scoring can provide standardised and consistent decision making across the bank's vast branch networks thereby allowing greater control.
Responsiveness	With credit scoring the banking policies and strategies can be updated quickly and efficiently.

(Source: Various)

Though credit scoring provides the above benefits some of its limitations (Churchill *et al.,* 1977; Mester, 1997; Stanton, 1999; MacNeill, 2000; Bhatia, 2006; Anderson,

2007) are summarised in Table 2.11 which provides a description on the limitations and how they could be dealt with.

Table 2.11: Limitations of Credit Scoring:

Limitations	Descriptions on the limitation and how to deal with these.
Complexity	Credit scoring models are complex and any errors made during the model development process might result in large losses. Due consideration has to be given to obtain a rich sample of both well-performing and poorly performing loans during the model development phase.
Selection Bias	While the model is being developed, the sample should include characteristics of both the accepted and rejected applicants. Otherwise this could lead to bias in the estimated weights in the scoring model. A good model needs to make accurate predictions in both good and bad economic times, so the data on which the model is based should cover both expansions and recessions.
Situational Information	Credit scoring models does not take into consideration the situational information about the personal or economic circumstances of the applicant. That is, these credit models typically are developed without any connections between the information in consumer credit records and information pertaining to the economic environment in which the consumers live or work or other contextual information about their personal circumstances. Thus, an applicant who has experienced credit problems for a short period due to economic downturn or a personal unfavourable condition such as medical emergency typically would be assigned a comparable score to an applicant whose credit problems reflect persistent excessive spending or a reluctance to repay debts. The stance for future performance on new or existing credit for these two individuals, other factors held constant may be quite different.
Qualitative Inputs	As the exposure gets larger, qualitative inputs such as local knowledge, macroeconomic conditions also become an important driver for credit risk. However, credit scoring only considers the quantitative inputs. So model developers should transform these qualitative inputs into modelling characteristics and incorporate in the model.

(Source: Various)

In the words of Barron and Staten (2003, p.11), *"credit scoring has affected the broader access to the credit market by making automated risk assessment possible"*. This is considered significant because though there might be some limitations, the benefits which could be derived from a credit scoring model are its objectivity, consistency, predictive accuracy, speed and mass customisation which is indispensable in the consumer credit industry.

2.7 Determinants of the Predictive Power of Credit Scoring Models:

The credit scoring models are built using statistical techniques. In this context the predictor variables are called the characteristics and the values that they can take are called the attributes. Using the credit scoring models, banks either accept or reject a credit applicant based on their credit score against the cut-off score as determined by its risk appetite which in practice differs among banks according to their credit policies. As time passes, populations changes as do the distribution of the credit applications, this phenomenon is referred as *'population drift'* by Hand and Henley (1997, p. 525). The models' predictive power might be lost if these changes in the population drift are not incorporated in a timely manner by updating and validating the model on a regular basis. Within the credit scoring industry, the predictive power of the credit scoring models are determined by factors such as account definition, characteristics or variables selection, time horizon, sample selection and reject inference, which are discussed below. Model developers have to consider the potential benefits that will arise from the model development process that have to be balanced against the costs of development, bearing in mind, data availability sometimes limited.

2.7.1 Account Definition:

The consumer credit industry approach to loan classification is to adopt a straight forward classification of account performance based on historical customer data.

Under this approach, *"a good account is one that you are glad you took and a bad account is one that you are sorry that you took"* (Lewis, 1992, p.36). In the case of a revolving credit, a good account might be someone whose statement of account might show that the account has been active for a minimum of 10 months, there has been at least three purchases being made using the account and there has not been one period of 30 days delinquent in the past 24 months. On the same note, a bad account might be delinquent for 90 days or delinquent three times for 60 days in the past 12 months or indeed has been bankrupt (Lewis, 1992). However, Avery *et al.,* (1996, p.621) have defined a delinquent account *"as being when a borrower fails to make a scheduled payment on a loan. Since loan payments are typically due monthly, banks customarily categorises delinquent loans as 30, 60, 90, or 120 or more days late depending on the length of time the oldest unpaid loan payment has been overdue".* It could be argued that default occurs, technically at the same time as delinquency; that is, a loan is in default as soon as the borrower misses a scheduled payment.

Further, Sidiqqi (2005) defines a category of "Indeterminate" accounts as those account which do not conclusively fall into either the "good" and "bad" categories. It could be argued that the indeterminate accounts do not have sufficient performance history for classification, or are subject to some mild delinquency with roll rates neither low enough to be classified as good nor high enough to be bad. Thus, for the model development purposes, a major problem could arise from including indeterminate accounts as they might create the potential for misclassification. Clearly, assigning a classification of "good" to an account that has insufficient performance can result in misclassification and the underestimation of bad rates.

Thus, account definition could be summarised into three basic groups: "bad", "good" and "indeterminate" as presented in Table 2.12.

Table 2.12: Account Definition:

Type of Account	**Descriptions**
Bad	The Basel Committee on Banking Supervision (2001, p. 28) has defined an account to be "bad" or in "default": *"If the obligor is unlikely to pay its debt obligations (principal, interest or fees) in full"*; or *"A credit loss event associated with any obligation of the obligor such as charge-off, specific provision, or distressed restructuring involving forgiveness or postponement of principal, interest or fees has happened"*; or, *"The obligor is past due more than 90 days on any credit obligation"*; or *"The obligor has filed bankruptcy or similar protection from creditors"*. If the lender's objective is to increase profitability, then the definition must be set at a delinquency point (30, 60, 90 or 120 days) where the account becomes unprofitable (Sidiqqi, 2005). The definition should be based upon the product or the purpose for which the model is built. For example, bankruptcy, fraud, claims (claim over $1,000 and collections (less than 50 percent recovered within three months) (Sidiqqi, 2005).
Good	For an account to be classed as "good" Siddiqi (2005) has listed the following conditions: The account has not been subjected to being delinquency at any point, the account is always profitable and has a positive Net Present Value (NPV), and there have been no claims, no bankruptcy filed, and no fraud on the account.
Indeterminate	Indeterminate account might have the following characteristics (Sidiqqi, 2005): The account has hit the 30 or 60 day delinquency but this does not roll forward, or the account has been inactive or voluntarily cancelled, or the account has been approved but has insufficient performance history for classification, or account with insufficient usage- for example credit card accounts with high unused credit balances.

(Source: Various)

2.7.2 Characteristics or Variables Selection:

A critical part of preparing the sample data for analysis to develop the credit scoring model concerns the selection of the characteristics or variables to be included as part of the statistical technique to derive the model. Lewis (1992) cites that for the characteristics to be useful in the model, they should be identified on the credit application form which would be used when the scoring system is live. Bunn and Wright (1991) highlighted that the main challenge in the selection of characteristics by model developers is to get an overview of the key variables which the experts think to be important in the credit decision making process. Hand and Henley (1997) supported this by adding that using expert knowledge and experience in order to identify the key variables would provide a good complement to the formal statistical manipulations.

Thus, one of the first steps to be taken, before the model development process, is to consult with the credit teams and experts to identify the characteristics which could be included in the model. This consultative process would not only improve the final model but also add to the model reliability and robustness. Several other factors such as the variables predictive power, informational content, correlations (if the variables are highly correlated, then they might not add any value to the model), the variables availability over a period of time, the legal and ethical compliance (for example, variables related to race, culture, religion, nationality are not included in the model) should all be taken into consideration (Siddiqi, 2005; Anderson, 2007).

Thus, the objective of the characteristics selection process is to improve the model's prediction performance, to provide reliable and cost-effective predictors and also to provide a better understanding of the underlying data generation process. Typically characteristics which the lenders gather information from the application forms could be grouped as demographic, financial, employment and behavioural characteristics. The typical characteristics used in the application forms of the Nepalese banks which could be replicated within the credit scoring models are presented in Table 2.13.

Table 2.13 Typical characteristics used in application forms:

Demographic	Financial	Employment	Behavioural
1. Age of the borrower. 2. Sex of the borrower. 3. Marital Status of the borrower. 3. Number of dependents. 4. Residential status. 5. Current Address	1. Total assets of borrower. 2. Gross income of borrower. 3. Gross income of household. 4. Monthly costs of household.	1. Type of employment. 2. Length of employment. 3. Number of employment over the last 'x' years.	1. Whether the borrower has a checking account. 2. Average balance on the checking account. 3. Any outstanding loans. 4. Any loans defaulted or delinquent. 5. Collateral/Guarantees.

(Source: Illustrative example developed for this research based on the application forms of Nepalese banks and the professional experience of the researcher)

2.7.3 Time Horizon:

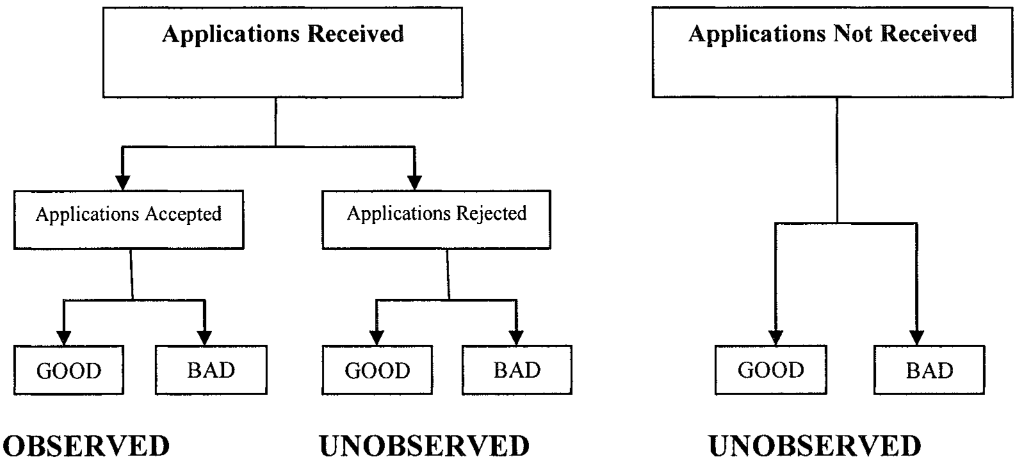
Within the literature, it has been established that credit scoring models are developed using historical data from the credit files of customers who have previously been granted credit. Thus, one of the important determinants for a powerful credit scoring model is the time horizon of the historical data in which it has been built. With respect to the determination of the appropriate time period, the Basle Committee on Banking Supervision (1999, p. 17) has advocated for a credit risk modelling horizon of one year because during this period *"new capital could be raised; loss mitigation action could be taken to eliminate risk from the portfolio; new obligor information can be revealed, default data may be published; internal budgeting, capital planning, accounting statements are prepared; and credits are normally reviewed for renewal"*.

However, the application and behavioural scoring models have different interpretations with respect to the time horizon from which the data has been collected (Liu, 2001; Bhatia, 2006). For application scoring models, a time horizon represents the time between the application and the good/bad classification, which is about 12-18 months (Bhatia, 2006) or 18 months (Liu, 2001). And in the case of behavioural scoring models, the performance of the account over a period of 12 months (Liu, 2001) is taken into consideration in addition to the application characteristics. Further, for home loans, Bhatia (2006) reported that the information related to any pre-payment behaviour should be measured for every sub-part of the portfolio on a year by year basis. Thus, it could be argued that the time horizon of 12 months might be appropriate to be considered in model development as it normally takes this period for the default status to show up.

2.7.4 Sample Selection and Reject Inference:

A credit scoring model is developed from a sample of applicants who have been granted credit and whose outcome has been observed over a period of time. This sample is biased towards the applicants who are eligible for credit; however, it is not unbiased when applied to the entire population of applicants seeking credit. The bias introduced in the scoring model is that the applicants who never applied for the loan and applicants who are rejected (both of which are unobserved cases) are not considered in developing the credit scoring models (Greene, 1998). This sample selection bias may have implications for model accuracy and its general applicability (presented in Figure 2.2).

Figure 2.2 Sample Selection for Credit Scoring



(Source: Adapted from Lewis (2002) An Introduction to Credit Scoring)

The process of reject inference has been dealt with by other authors by making adjustment for this sampling bias during the process of model development by taking into consideration *"how the rejected applications would have performed if they were accepted and this process is known as reject inference"* (Lewis, 1992; Hand and Hanley, 1997; Bhatia, 2006; Banasik and Crook, 2007). The process of reject inference means making inferences about the sampling population for the rejected applications. Thus, the scoring system which is built by taking into consideration the rejected applicants' details would serve the entire population in the most effective way (Lewis, 1992).

In the literature various techniques have been employed to deal with reject inferences. Hand and Henley (1997) and Banasik *et al.,* (2005) made use of the random supplementation technique in which the applicants which would be rejected are being accepted in the model building process. Hand and Henley (1997) argued that the process of random supplementation would be ideal for reject inference but it would be very too risky for the lender. The second technique refers to augmentation

(Hsia, 1978; Siddiqi, 2005). In the augmentation process, the model which has been built on accepted cases is then applied to the rejected cases to get a new probability of default. Once the cut-off probability which classifies the rejects as good or bad credit risk has been determined, this information is added back to the original model and remodelling is done incorporating the reject cases. However, augmentation has been disapproved of by several authors (Hand and Henley, 1997; Banasik *et al.*, 2005) citing that the functional form of the model (that is, Probability(b/X), where 'b' denotes a bad loan and 'X' the independent variables is the same for the accepted and rejected applicants) is not compatible with making any reject inference.

A third technique proposed by Joanes (1993) refers to the interactive classification in which the augmentation technique described above is repeated until the model is predicting the same in both accept and reject regions. It could be argued that as the classification rule is developed from the accepted applicants, the major problem might be its domino effect. Thus, Crook and Banasik (2002, p.858) argues by stating that *"very little have been published that empirically compares the predictive performance of models that incorporates different possible reject inference techniques"*. Lately, a fourth technique known as "Cohort Performance" has been proposed by Anderson (2007) in which information on the rejects available through another lender who has granted credit might be incorporated in the model. The cohort performance might be in the form of a score or the account status. Though, this technique might provide the reject inference in the model, there is no relevant literature discussing its practical effect. Thus, while all of the above reject inference techniques may provide value to the model developer, it could be argued that there is nothing that can replace having the entire population taken for modelling purposes.

2.8 An Overview of the Statistical Techniques used for Credit Scoring Models:

According to Crook et al., 2007, over the 20 years the techniques used for developing credit scoring models were based on statistical and operational research tools, which were regarded as its most successful and profitable applications within the credit scoring industry. Various authors have assigned different aims for building the credit scoring model. According to Hand (1998) and Thomas (1998), the aim of building the model is to formulate the best tool for classifying applicants for credit. On the other hand, Lee, Chiu, Lu and Chen (2002) put the aim as being to assign credit customers to either good credit or bad credit. And Lim and Sohn (2007) say that credit scoring model is designed to predict the bad credits. Thus, it could be summarised that the aim of the credit scoring model is to classify, as well as forecast, applicant for credit quality.

Although fundamentally, statistical and operational research techniques, such as discriminant analysis, linear regression analysis, logistic regression, neural networks, survival analysis, classification and regression trees have been used in building the scoring models (Orgler, 1971; Boyes, Hoffman and Low, 1989; Hand and Henley, 1997; Greene, 1998; Banasik, Crook and Thomas, 2001), the selection of the most appropriate technique employed in this study was informed by the availability of data and the consideration outlined in section 2.7. In light of these, the appropriateness of each of the alternative model development techniques that could have been employed is reviewed within the next sections.

2.8.1 Discriminant Analysis (DA):

Fisher (1936) first proposed discriminant analysis as a discrimination and classification tool. Discriminant Analysis (DA) is a statistical technique that is used in modelling classification tasks (Lee, Sung and Chang, 1999) to predict group membership from a given set of predictors (Sharma, 1996; Tabachnick and Fidell, 2001). With regard to the statistical assumptions in implementing discriminant analysis, Tabachnick and Fidell (2001) explain that the data has to be independent and normally distributed while the covariance matrix needs to be homogeneous.

Apilado *et al.,* (1974, p.275-283) applied discriminant analysis to construct their credit scoring models and states that *"discriminant analysis....firstly distinguishes among group and identifies group differences; secondly, it classifies existing and new observations into predetermined groups, and finally, it identifies the key variables that contribute the most to the discrimination among groups".* Discriminant analysis was used as a credit scoring tool first by Durand (1941) to produce good predictions of credit repayment. Extensive use of discriminant analysis to build credit scoring models for general bank and credit card sectors has been carried out by Eisenbeis (1978), Martell and Fitts (1981), Grablowsky and Talley (1981), Reichart *et al.,* (1983), Titterington (1992), Desai *et al.,* (1996), Bardos (1998) and Lee *et al.,* (1999).

The linear combinations for a discriminant analysis are derived from an equation that takes the form:

$$\mathbf{Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_n X_n} \qquad \textbf{(Equation 2.2)}$$

Where, Z represents the discriminant (named as Zed) score
α is the intercept term
β_i represents the respective coefficient in the linear combination of the explanatory variables, X_i for $i = 1,\ldots..,n$ (Lee *et al.,* 2002)

This leads to the construction of a model that allows for being able to best predict to which group a given variable belongs. It is significant to note that there is little in the theoretical construction to support the choices in the variable selection; the variable selection is purely based on the best statistical fit. The model can be built step by step, where all available variables are reviewed and evaluated at each step to determine which contributes the most to discriminating between groups. It tries to derive the linear combination of two or more independent variables that will best discriminate between a *priori* defined groups (for example, good or bad credit risk). This is achieved by the statistical decision rule of maximising the between-group variance relative to the within-group variance. This relationship is expressed as the ratio between the two. Malhotra and Malhotra (2003) adds that in order to construct the classification matrix, an optimum cut-off score which is called the Z-score based similar to the work of Altman (1968) has to be identified. These cut-off score is selected in order to minimise the risk of misclassification, which might lead to two types of error, Type I error occurs when a bad credit applicant is classified as a good credit applicant. A Type II error occurs when a good credit applicant is classified as a bad credit applicant. For lending decisions, clearly a Type I error is more critical than a Type II error.

2.8.2 Linear Regression:

Linear regression is the process of establishing the relationship between one dependent variable with one independent variable (simple linear regression) or with several independent variables (multiple linear regression). A linear transformation of the independent variables (say, X) is done so that the sum of squared deviations of the observed and predicted (say, Y) is minimised.

Simple linear regression is given by:

$$Y = \alpha + \beta X + \varepsilon \qquad \textbf{(Equation 2.3)}$$

Multiple linear regression is given by:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_n X_n + \varepsilon \qquad \textbf{(Equation 2.4)}$$

Orgler (1970) proposed a credit scoring model for commercial loans using linear regression analysis and later (1971) used it to construct a scorecard for the evaluation of outstanding consumer loans, rather than screening new applicants. Orgler (1971) found that the behavioural variables were more predictive of future credit quality than the application variables. Orgler (1971) concluded from the modelling process that linear regression models could be used by banks for periodic consumer loan reviews. According to Hand and Henley (1997) since the evaluation of outstanding loans includes information about how the customer has performed so far, it is a behavioural scoring model. Crook *et al.,* (2007) argues that with linear regression making assumptions about linearity and normally distributed target variables, the predicted probabilities could lie outside the (0, 1) range. This might not be problematic if the purpose is to rank the probabilities of default. However, for application screening and capital adequacy purposes, linear regression might not serve the purpose.

2.8.3 Logistic Regression (LR):

The typical characteristics used in credit scoring models (as in Table 2.6) varies from being continuous (may take any value, for example monthly income of the applicant), categorical (may take a discrete value, for example sex of the applicant) or both. As reported by Crook (1997) and Thomas (2000), application scoring requires the characteristics to be categorical (that is to have two discrete classes: accept and reject applicants), which is not possible with discriminant analysis and linear regression as the normal distribution is violated when categorical characteristics are used. In order to address this problem, logistic regression may be used with a dependent characteristic that is binary (a categorical variables that has two values such as 'yes' and 'no' or 'zero' and 'one') and the independent characteristics are continuous, categorical or both.

In one of the first published accounts of logistic regression applied to credit scoring in comparison with discriminant analysis, Wiginton (1980) concluded that the logistic regression approach gave superior classification results. Using logistic regression for commercial and industrial credits Srinivasan and Kim (1987) obtained a classification accuracy of 89.3 percent. Logistic regression has been widely used for application scoring where the probability of binary outcomes (zero or one) is related to a set of potential predictor characteristics. It uses a process called maximum likelihood estimation (MLE) which transforms the dependent characteristics into a log function, makes an estimate of what the coefficient should be and determines changes to the coefficients to maximise the log likelihood. The logistic regression formula takes the form of Equation 2.5:

$$\log [p (1 - p)] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_n X_n \qquad \textbf{(Equation 2.5)}$$

where, p is the probability of the outcome of interest,

α is the intercept term, and

β represents the respective coefficient in the linear combination of the independent variables (X).

The dependent variable (Y) is the logarithm of the odds, {log [p (1 - p)]}, which is the logarithm of the ratio of two probabilities of the outcome of interest (Lee *et al.*, 2002). Given the set of independent variables, the probability of the value of one for the dichotomous outcome is (Desai *et al.,* 1996):

$$\mathbf{Z = 1/\,(1\text{-}\ e^{-Z})} \qquad \textbf{(Equation 2.6)}$$

Where, Z= the probability that the dichotomous outcome is one, and

$$\mathbf{Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_n X_n} \qquad \textbf{(Equation 2.7)}$$

Thus, the objective of the logistic regression model in credit scoring is to determine the conditional probability of a specific observation belonging to a class, given the values of the independent variables of the credit applicants (Lee and Chen, 2005). Logistic regression has been accepted as the most accepted statistical technique for developing credit scoring models because: it is specifically designed to handle a binary outcome in which the final probability cannot fall outside the range of zero to one. Further, it provides a fairly robust estimate of the actual probability, given available information (Lee and Chen, 2005; Crook *et al.,* 2007)

Within the literature an extensive use of logistic regression to develop credit scoring models for personal loans, business loans, credit cards and mortgages has been explored by Joanes (1993), Henley (1995), Asch (1999), MacNeill (2000), Westgaard and Van der Wijst (2001) and Al Amari (2002).

2.8.4 Decision Trees/Recursive Partitioning Algorithm:

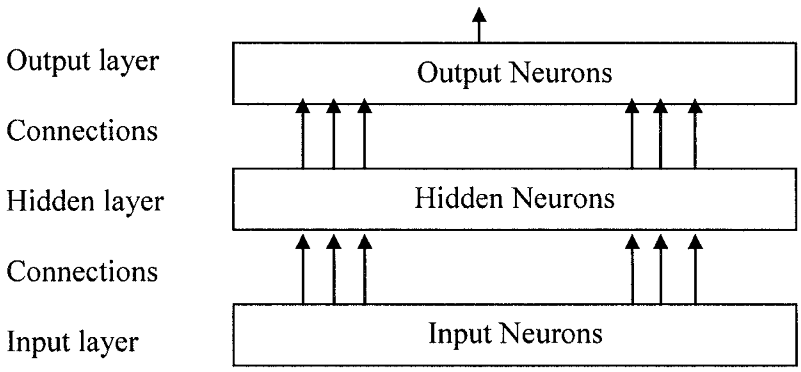
Decision trees/Recursive partitioning algorithm are non-parametric classification techniques which employ graphical tools, with branch or root like structure boxes and lines used to show possible turns of events that may be controllable. They are used for data visualisation in classification and prediction problems (Dimitras *et al.,* 1996; Anderson, 2007). For example, considering a database of credit applicants described by 'n' characteristics: x_1, x_2, x_3.......x_n. These applicants belong to two classes which will be denoted by "good credit risk" and "bad credit risk". The main aim of the credit scoring model is to develop a classifier which would separate the good credit risk sample from the bad credit risk sample.

Using the decision tree, a recursive partitioning algorithm could be constructed which begins with a root node containing a sample of both types of applicants in which the distance between the good credit risk applicants is minimised and the distance between the good and bad credit risk applicants are maximised. The algorithm loops over all possible binary splits in order to find the attribute 'x' and corresponding cut-off value 'c' which gives the best separation into one side having mostly good credit risks and the other mostly bad credit risks (Breiman *et al.,* 1984; Frydman *et al.,* 1985; Davis *et al.,* 1992). Decision trees have been used in the credit scoring industry as a classifier when the amount of data is limited (Frydman *et al.,* 1985; Davis *et al.,* 1992). The main strong point in using decision trees is in its ability to identify patterns which are transparent in the case of simple trees. However, as the trees become complex and bushier, there are fewer cases in each node, bringing with it the potential for overfitting and unreliable results (Anderson, 2007).

2.8.5 Neural Networks:

Neural networks are classification algorithms which work like a human brain processing information and consist of the input, hidden and output layers of interconnected neurons (Nelson and Illingworth, 1990). It's essential characteristics are the nodes, the network architecture describing the connections between the nodes and the training algorithm used to find the values of network weights for a particular network (Haykins, 1999; Lee et al., 2003; Crook et al., 2007). For example, the input layers might be the applicants' characteristics (independent variables) and the output might be the solution to the problem which is good credit (0) or bad credit (1) risk, with numeric values assigned to it. The output is calculated by using the weights expressing the relative importance of each input to the processing elements. The neural network through repetitive adjustment of the weights learns and identifies its correct value (Malhotra and Malhotra, 2003).

Figure 2.3 A Typical Framework of Neural Networks:



(Source: Malhotra and Malhotra (2003) Evaluating consumer loans with neural networks)

In credit scoring, neural networks build upon an artificial intelligence algorithm which tries to establish the relationship between the probability of default and the applicant's characteristics, thus segregating the most important default predicting characteristics. Within the literature, neural networks have been used to design credit scoring models by Rosenberg and Gleit (1994), Desai *et al.,* (1997), Hand and Henley (1995), West (2000), Malhotra and Malhotra (2003). However, Crook *et al.,* (2007) argues that in the UK and US, where the rejected applicants are given a reason for being rejected, neural networks as a credit scoring technique are not preferred as the resulting set of classification rules generated are not easily interpretable in terms of the original input variables.

2.8.6 Which is the most appropriate technique for Credit Scoring Model Development?

An important concern for model developers is to decide on the appropriate technique to use in credit scoring model development. Each of the techniques described above have their own merits and demerits and while making the choice, certain aspects relating to the modelling technique has to be taken into consideration (Hand and Henley, 1997; Crook *et al.,* 2007; Anderson, 2007), because the final credit scoring model has to be tailored to obtain the relevant type of credit scores as already presented in Table 2.5. The modelling considerations embrace general conditions such as suitability of the technique for the task at hand, the development speed and its user friendliness in terms of the ease to develop, learn and apply. It is also important to determine the model adaptability. Finally, as with all risk models, the output transparency is important so that the users are able to understand the assumptions incorporated in the models and detect any inaccuracies encountered.

In their seminal work, Hand and Henley (1997) presented a critical analysis of the statistical technique used in credit scoring models and conclude that there is no overall best model, for what is best depends on the objective of the classification, the data structure and the characteristics used. Enhancing and building upon this, in one recent published document, Crook *et al.,* (2007) presents an overview of the relative predictive accuracy (percentage correctly classified) of some of the different modelling techniques (presented in Table 2.14).

Table 2.14 Relative Predictive Accuracy of Different Modelling Techniques (in per cent):

Author	Linear Regression	Logistic Regression	Decision Trees	Neural Networks
Srinivasan and Kim (1987)	87.5	89.3	93.2	
Boyle *et al.*, (1992)	77.5		75.0	
Henley (1995)	43.4	43.3	43.8	
Desai *et al.*, (1997)	66.5	67.3		66.4
Yobas *et al.*, (2000)	68.4		62.3	62.0
West (2000)	79.3	81.8	77.0	82.6
Lee *et al.*, (2002)	71.4	73.5		73.7
Baesens *et al.*, (2003)	79.3	79.3	77.0	79.4
Ong *et al.*, (2005)	80.8		78.4	81.7

(Source: Crook *et al.*, (2007) Recent developments in consumer credit risk assessment)

Table 2.14 is significant as it shows that most predictive techniques provide fairly similar predictive accuracy and therefore the choice might be related by some other factors. For example, lenders who have a long history of credit scoring have been found to use the linear techniques and discriminant analysis, where the focus is to establish group membership in which the predicted probabilities can lie outside the range (0,1) (Srinivasan and Kim, 1987; Boyle *et al.,* 1992; Henley, 1995; Crook *et al.,* 2007). However, when the lenders wanted a score with an estimated probability of default (PD), such as would be required for capital adequacy purposes, Logistic Regression (LR) is widely used (West, 2000; Lee *et al.,* 2002; Baesens *et al.,* 2003). Non-parametric techniques such as neural networks and decision trees which are also known as the expert systems (Thomas, 2000) have been applied in scoring of corporations, where there is less data available, than in consumers scoring (Baesens *et al.*, 2003; Ong *et al.,* 2005).

Thus, the lender is posed with the question: which is the most appropriate techniques for credit scoring model development. In such situation, Thomas (2000) and Crook *et al.,* (2007) have recommended that if a lender is developing credit risk models for the first time, then it should use logistic regression because it is specifically designed to handle a binary outcome, the final probability cannot fall outside of the range 0 to 1 and it provides the probability estimates of classification more accurately. Given the specific circumstances of this study which involve no history of credit scoring, combined with limited customer data within the Nepalese banking sector, the most appropriate technique according to the literature to develop the credit scoring model would be logistic regression.

However, it is also important to consider why credit scoring models used by banks in other emerging or developed markets are not suitable for Nepalese banks. Within the emerging markets (Brazil, Russia, India and China- BRIC), evidence from the literature suggest that lenders have been recently developing credit scoring models (de Andrade and Thomas, 2007; Kordichev and Katilova, 2007; Rao, 2005; Thanh and Kleimeier, 2006). These are known to be based on small databases which have used logistic regression and are still to establish dominance within the credit scoring industry in their own countries. With reference to the more developed markets such as UK and US, the models were built on more mature customer and credit bureau databases and as a result have been developed to a more sophisticated level than is needed in the Nepalese banking sector. Moreover, the customers characteristics (for example, income level, repayment behaviour, and long credit history) on which these models have been built in developed markets are different from the Nepalese market. Also, the credit information centre data that is available within the Nepalese banking sector has not so far been used for the credit decision making process by Nepalese banks because it is used only for blacklisting borrowers and not to classify new applicants for credit (Ramamurthy, 2004; Credit Information Centre, 2008). So the transferability of either the developed or emerging markets models to the Nepalese banking sector is ruled out. Thus, it is imperative that the credit scoring model be built taking into the modelling consideration and nature of the data availability from the Nepalese banks as such a model would be considered robust and appropriate.

2.9 Credit Scoring Modelling Issues:

According to Anderson (2007, p. 457), *"Credit scores are powerful tools, but they are not a panacea"*. In order that the credit scoring models are used as intended, certain modelling issues such as model overrides, model performance and validation needs to be addressed. This section provides a critical discussion on these credit scoring modelling issues.

2.9.1 Model Overrides:

The primary purpose of the scoring system is to guide the lender to make an objective credit decision. However, one of the challenges to objectivity is that it remains possible to make subjective overrides wherein the credit decisions arrived at through the automated system might be reversed or changed. These changes to the credit decisions (either positive or negative) as reported by Lewis (1992) are referred to as "Overrides". They occur either through policy rules which are set out by the lender for a specific applicant group or through individual decisions based upon additional information available in respect of the applicant. Evidence from the literature (Lewis, 1992; Siddiqi, 2005; Anderson, 2007) indicates the following situations in which the overrides might take place:

1. *Informational Overrides:* these are overrides which take place based upon any new information about the applicant which has not been incorporated at the time when credit scoring was done. For example, if the applicant has just won a lottery or had an inheritance or had been blacklisted. In such circumstances, the credit decision might change, however the likelihood of this event might of rare. Further, Lewis (1992) argues that in the case of transactional lending it is rare that the credit evaluator might recognise the identity of the applicant and informational overrides tend, therefore to be ruled out. However, it could be argued that in the case of relationship lending, informational overrides might take place as the credit assessor is in direct contact with the applicant, which might influence the credit decisions. Further, Anderson (2007, p. 459) argues that *"overrides are part and parcel of the credit decision process"*, in high-value/low-volume lending situations in which credit scoring is a new concept and the role of credit officers are not ruled out.

2. *Policy Overrides:* a more or less common occurrence, policy overrides take place whenever new sets of rules are in place for a special customer group. For example, credit might be granted to students at the local university, even if they might not have a good score, taking into consideration the long term source of business for the bank. There might be other instances wherein there is a change in the lender's policy regarding the minimum age and other legal requirements, which might trigger policy overrides. Further, the governments in underdeveloped or developing countries might introduce legislation for granting

credit to certain sections of the society, in which the lenders have to comply by adopting policy overrides.

3. *Intuitional Overrides:* are overrides which might occur whenever the credit evaluator or officer might reverse the decision which has been arrived through the scoring system. There might not be any justification for such reversal. The credit officer might, through his experience, think that the applicant is a good or bad credit risk. Lewis (1992) have noted that some financial institutions might give the credit officers specific authority to override the credit scoring system within a certain threshold limits. It could be argued that with the introduction of the automated system there should not be any intuitional overrides.

Overall, though overrides dilutes the credit scoring effectiveness, the lenders should make every effort to identify the different types of overrides and make sure that the credit decisions are free from overrides for consistency and reliability.

2.9.1 Model Performance and Validation:

Clearly, one of the key challenges in developing a credit scoring model is to ensure that the model works as anticipated. According to Bhatia (2006, p. 406) "*validation is a process to assess the performance of risk component measurement systems consistently and meaningfully*". Validation not only increases the trustworthiness of the model, but it also helps the enhancement of the model's strengths and weaknesses among management and user groups. The performance of the model is related to the model predictive power (that is to rank group according to the risk) and the model predictive accuracy (that is whether the model provides a consistent estimates of good and bad rates). Thus, validation aims at establishing consistency and accuracy of the credit scoring model performance over a period of time.

A number of studies (Burns and Ody, 2004; Hand, 2005; Bhatia, 2006) have focussed on this aspect. Burns and Ody (2004, p. 6) have argued that *"given the economic implications associated with a model's accuracy and effectiveness, issues concerning model validation and performance are of obvious concern to the industry"*. Obviously, if the model has an error, it might lead to revenue losses through poor customer selection (credit risk) and collections management. Concurrently, the best practice is that once the model has been developed it has to be validated so as to ensure that the model performance is compatible in meeting the business as well as the regulatory compliance needs. Against this background it is not surprising that much of the literature in this area reflects the requirements set out by the Basel Committee on Banking Supervision (BCBS). In one of its paper on the validation of the internal ratings systems (BCBS, 2005, p.4), the salient features are noted as:

- *"Validation's fundamental purpose is to assess the validity of risk estimates and their use in business processes, which should cover both quantitative and qualitative elements"*,
- *"Lenders are responsible for their own validation and there is no universal accepted validation method. However, the validation process and its results should be independently reviewed"*.

This is important as while noting the overwhelming significance of validation, they do not recommend on how it should be done. Bhatia (2006) goes someway to addressing this by noting that validation could be done by identifying any missing data in the sample, and properly addressing the issue of missing data management; by identifying omitted characteristics, which might result due to the correlation assumptions; by verifying the correlation matrix so as to check if the correlation is consistent for the time horizon in respect of the risk component being measured; by considering if the statistical technique is widely used and appropriate for modelling purposes; and by calibrating the model. The performance of the model could be ascertained by calculating the classification accuracy generated by the model using the percentage of correctly classified (PCC) as presented in Table 2.15. This approach has been widely applied within the literature by Srinivasan and Kim (1987), Boyle *et al.,* (1992), Henley (1995), Desai *et al.,* (1997), Yobas *et al.,* (2000), Lee *et al.,* (2002), Baesens *et al.,* (2003) and Ong *et al.,* (2005).

Table 2.15 Classification Accuracy of Credit Scoring Models

		Predicted		
		Quality of the Loan		
Observed		Default/Bad Credit	No Default/Good Credit	Percentage Correct
Quality of the Loan	Default/Bad Credit	Bb	Bg	PCC bad
	NoDefault/Good Credit	Gb	Gg	PCC good
	Overall Percentage			PCC total

In the Table 2.15, Bb represents the number of correctly classified bad credit whereas Bg represents the number of bad credit that are incorrectly classified as good credit. Correspondingly, Gg represents the number of correctly classified good credit whereas Gb represents the number of good credit that are incorrectly classified as bad credit. The percentage of correctly classified bad credit (PCC bad) is defined as the proportion of correctly classified bad credit to the total number of observed bad credit and is given as PCC bad = Bb/ (Bb + Bg). The percentage of correctly classified good credit (PCC good) is defined as the proportion of correctly classified good credit to the total number of observed good credit and is given as PCC good = Gg / (Gg + Gb). Thus, the overall percentage of correctly classified by the model is defined as the number of correctly classified credit relative to the total number of credit given as PCC total = (Bb + Gg) /(Bb + Bg + Gg + Gb). This classification measure is easy to use; however it assumes that the costs of misclassification are equal and might result in two types of errors, such as:

•Type I errors: bad credit classified as good (Bg).

•Type II errors: good credit classified as bad (Gb).

From the bank's perspective, it would want to minimise both type of errors, however the most significant in terms of the bank's profitability is the type I errors. Therefore, Baesens *et al.*, (2003) developed this approach by incorporating additional accuracy measures named as sensitivity (SENS) and specificity (SPEC). Sensitivity (SENS) is defined as the proportion of correctly classified good credit to the total number of predicted good credit which is given as, SENS = Gg / (Gg + Bg). Specificity (SPEC) is defined as the proportion of correctly classified bad credit to the total number of predicted bad credit which is given as, SPEC = Bb/ (Bb +Gb). This is important because the cost of bad credit classified as good credit (Bg) will be higher than the cost of good credit classified as bad credit (Gb), and hence the credit scoring model could be calibrated based on the sensitivity (SENS) measures.

Within the literature, other statistical techniques used for model performance and validation include the Kolmogorov-Smirnov (KS statistic), the Gini Coefficient (GC), the Mean Difference (t-statistic) and the Information value (or divergence)

(Burns and Ody, 2004; Bhatia, 2006; Hand, 2005). These are not discussed as they are advanced and sophisticated techniques which require a mature, large customer database and are thus beyond the scope of this research.

2.10 Conceptual Framework of the Research- Home Loans:

Earlier in the chapter, the theoretical developments relating to credit scoring in the consumer credit decision process along with the different modelling techniques and issues relating to credit scoring models are discussed. The remainder of this chapter is focussed on the conceptual framework of the research which is related to home loans. In the consumer credit industry the terms "Home Loans" and "Mortgages" have been used interchangeably and signify the same type of lending. The Council of Mortgage Lenders, UK (no date) defines, a mortgage "*as a loan which is secured against the home in which the borrower agrees to pay the loan back with interest over a period of time. In case, there is a default on the payment the mortgage lender can sell the home to recover the debt*". There are a number of key features which differentiates home loans from other consumer loans, these have been summarised as (Brennan, 1993):

1.***Collateral*** - In a home loan, the property underlying the loan forms the security in favour of the lender. The valuation of the collateral corresponds to an essential element in the credit approval process and as a result has an impact on the overall credit risk assessment. The characteristics of the property do influence propensity to default. For example, if the market value of the property is more than the loan amount, then the rate of default is low and vice versa.

2.***Term*** - the term of a home loan is typically 25 years. This extended term makes prediction of outcomes more complex because the credit is outstanding for a long period of time and in this period the personal circumstances of the borrower would change a number of times (a consumer loan is normally for 1-2 yrs).

3.***Amount*** - the value of the home loan is significantly greater than other consumer loans. Thus, the risk of loss which can result from each incidence of default is potentially higher. However, since there is an element of the borrower's equity in the purchase of the house, the default risk is minimised. Typically, the borrower's equity is 30% of the value of the property, but this obviously changes according to changes in the market conditions.

According to Lea (2000), *"the traditional model of a home loan is the portfolio lending model in which the lender performs the major functions of origination, servicing, funding and portfolio risk management"*. Booth and Walsh (2001, p.32) add to this by saying that *"home loans are a form of risk finance provided by banks and other financial institutions for the ownership of the property"*. Supplementary to this definition is the one given by Mari and Reno (2005; p.83), "*the home loan can be regarded as the portfolio of defaultable zero coupon bond issued by the debt-holders, then valuation can be accomplished via a linear combination of defaultable zero-coupon bond prices"*. Both these definitions consider the component of "*default and risk*". Thus, from the literature it could be summarised that in the assessment of home loans, considerations has to be given to the dual parameters of default and risk.

2.10.1 Risk of Default in Home Loan:

A home loan might be in the default status when the borrower is unable to service the loan with timely payment of the interest and principal or there might be a fall in the value of the property below the amount of the loan (Booth and Walsh, 2001). The main cause for this default may be attributed to the loss of borrower's income which may be as a result of the loss of job or being insolvent. *"Practically, when payments are first missed, the lender considers that the borrower is only delaying payment temporarily with the intention of renewing payment in the future, which means that the account is delinquent"* (Quercia and Stegman, 1993, p. 28). However, from the practice point of reference if payments are not met for a number of periods (typically three), then the lender considers that the borrower has decided to stop payment completely meaning that the account is in default (Giliberto and Houston, 1989). Technically and importantly for this study, a home loan is in default if it is overdue for more than 90 days (Basle Committee Banking Supervision, 2005).

Gau (1978) has cited that the main determinants of a default are functions of the borrower, property and financial characteristics.

1. ***Borrower Characteristics***: In a home loan, the borrower's income has been considered as the important determinant of the default. There is an inverse correlation between the stability of the borrower' income and the probability of default (PD). Among other borrower's characteristics which might influence default is occupation, number of years employed in the present job, the ratio of the primary borrower base income to the total family income, the number of dependents and previous experience with credit purchases.

2.***Property Characteristics:*** For home loans, the prime security is the value of the property which serves as the collateral for the loan. Home loans are secured for the lender because in case of default, the lender is able to recover the loan amount through the sale of the property. However, if the lenders' valuation of the property is higher than the market's appraisal, then the borrowers in periods of financial adversity may be unable to sell the property at a price equivalent to the remaining loan obligations thereby increasing the likelihood of a default.

3.***Financial Characteristics:*** The loan-to-value (LTV) ratio of the home loan determines the equity commitment of the borrower. Lea (2000) has argued that "*the amount of the borrower's own funds invested in the property also referred to as borrower's equity, factor heavily into the lending decision*". If the borrower's stake in the property is very high then the propensity of default is low. Alternatively, if home loan is acquired to refinance an existing loan, then it might signal a higher probability of default (PD). From the lender's perspective, it is better that the loan does not default and therefore would look into ways of loan rescheduling.

In case the borrower defaults, the value of the property should be sufficient to cover the outstanding principal and interest on the loan. However, if the value of the property falls short of the outstanding amount of the loan then it would lead to negative equity which is regarded as a major component of home loan risk. In the UK markets, as early 1990s, when house prices fell, the home loan default rates were very high and the lenders were not able to raise funds through the sale of the property. Currently (2007-2009), as a result of the credit crisis, the home loan market is experiencing a negative equity. So to counter against home loan default, an alternative solution was provided through Mortgage Indemnity Guarantee (MIG), an insurance policy in the developed markets. The MIG protects the lenders against the value of the home falling less than the value of the loan. MIG is required if the loan-to-value (LTV) ratio is very high (that is about 90%), but varies from lender to lender (MacNeill, 2000).

According to Ozdemir and Boran (2004) financial institutions that offer home loans face two types of risks: the risk of default (which is that the customer would not honour his obligations); and prepayment risk (which is the possibility that the customer would pay off the loan outstanding earlier than the term of the loan because of the fall in a interest rates or a re-financing decision). In practice, the risk of default is higher than the prepayment risk; hence the concentration of the literature is on the risk of default. Within the literature, two theories of the risk of defaults in home loan dominate as proposed by Jackson and Kaserman (1980). The main postulates of these theories are:

1. *Equity Theory of Default:* states that *"borrowers base their default decisions on a rational comparison of the financial costs and returns involved in continuing (or discontinuing) the periodic payments on the mortgage loan obligation".* This suggests that borrowers maximise their financial gain or minimise the financial loss that results from this decision. This view implies a strict optimising behaviour by the borrower wherein they would refrain from default to preserve sufficiently positive housing equity.

2. *Ability-to-Pay Theory of Default:* which maintains that *"borrowers will refrain from defaulting as long as their income flow remains sufficient to meet the*

periodic payment without undue financial burden". This theory suggests a satisfying behaviour mode by the borrowers. It also posits that borrowers refrain from default as long as financial resources exist to meet the debt obligations. Further, it could be argued that with lower monthly payments, the default rate could be minimised.

Thus, the screening of the loan applications is a key process in minimising home loan risk as it ultimately affects the profitability and stability of the lender (Limsombunchai *et al.,* 2005). The assessment and valuation of the risk is an important part of the lending process for the lender. A good credit risk assessment system assists the lender to price the loan, determine the amount of credit to be granted, reduce the risk of default and increase the likelihood of debt repayment. This includes determining the financial strength of the borrower, estimating the probability of default (PD) and reducing the risk of non-payment to an acceptable limit.

2.10.2 Home Loan Assessment and Credit Scoring:

Home loan assessment is a process in which the creditworthiness and the risk profiling of the applicant are assessed taking into consideration the information provided by the applicant in the credit application forms (Straka, 2000; Lea, 2000). The assessment process assists the lenders to arrive at a decision whether to accept or reject applicants for credit. It involves dealing with credit evaluation, collateral evaluation, insurance and risk grading.

Straka (2000) argued that the assessment process should be in good order as it affects the lenders' profitability and the loan portfolio. According to Lea (2000), the main objectives of home loan assessment process are to estimate the probability of default; to ensure that all legal and financial requirements on the property are satisfactorily completed; and to meet regulatory requirements on safe and sound lending practices. Historically, in consumer lending decisions, lenders have been using the subjective criteria (such as Cs, CAMPARI and PARTS discussed earlier within the literature) as the benchmark to assess home loans (Staton, 1999; Straka, 2000; Lea, 2000). According to MacNeill (2000) lenders who use the subjective assessment methods cite a number of reasons such as the flexibility offered in which credit officers are able to make a credit decision based on local knowledge; personal attention in the collection of debts and arrears; cost-effectiveness when lending volumes are low, and the subjective system places a check and balances in the credit quality as a result of lending authority. From this it could be seen why this approach is still prevalent in the less developed consumer credit markets.

Though strong support has been made in the literature for the subjective assessment system (Staton, 1999; Lea, 2000; MacNeill, 2000) it is not immune to criticism. Some of its weaknesses (Capon, 1982; Lewis, 1992; Hand, 1998) arise from the fact that it is prone to credit errors, inconsistency in credit decisions across a range of applicants, high costs associated with training and employing credit officers, slow credit decisions process as every application has to be minutely screened, and the lack of quantification makes it difficult to assign the credit risk borne by the applicant.

In view of the above weaknesses posed by the subjective assessment process, an objective assessment process assisted by credit scoring may provide a solution, which has been usefully summarised within the literature. MacNeill (2000) has cited the incentives which the lenders could achieve through the administration of the objective assessment process are risk benefits, consistency and objectivity in credit decisions which could result in process improvements.

Globally, in the early 1990s, there has been a boom in the housing finance markets which have created the need for an objective assessment process in order to speed up the credit decision making process and the growth in applicants. Towards achieving this, lenders started to use credit scoring techniques to aid in the credit decision process. Within the housing credit sector, the earliest use of credit scores dates back to July 1995 when Freddie Mac, one of the two largest housing related government sponsored suppliers of mortgage funds in the US endorsed the use of credit bureau score in the mortgage origination process. This endorsement sent a message that the technology of credit scoring was no longer considered simply an experiment in risk assessment. Instead, it was a signal from the government sponsored enterprises that credit scoring was being perceived as an indispensible part of the lending process. Further, the US government ratification of the use of credit scores in mortgage lending came when the Federal Reserve published its own study of the statistical validity of credit scores in predicting mortgage defaults (Avery *et al.,* 1996). The Federal Reserve study presented a significant relationship between credit scores and credit performance. In the US mortgage industry, where lenders are carefully reviewing and documenting loan denials to ensure compliance with government fair lending requirements, the credit scores ability to objectively rank or order applicants by risk level gave credit assessors a head start in the process of assessing the loan.

In summary, the role of credit (mortgage) scoring provides a measure of the likelihood that a 25 years home loan with a 5-10 average life will default and cause a loss (Stanton, 1999). Increasingly, credit scoring has facilitated the lenders to adopt risk-based pricing (determining the rate of interest and loan amount) to make home loans decisions. Further, the lenders can extend credit without face to face contact with the customer (that is relationship lending would cease to exist and is being replaced by transactional lending). Lenders are also able to increase their lending volume as they could evaluate loans in minutes and close transactions within hours instead of days. Thus, credit scoring could help lenders by establishing an objective, consistent, fast home loan assessment system which is uniform in measure (Feldman, 1997).

Consistently, it is imperative to consider the drivers and impact on the home loan market, a credit scoring can provide. These have extensively been identified by Capon (1982), Hand (1998), Stanton (1999) and MacNeill (2000). It is the regulation of the financial authority of the country which explicitly states that that the banks must assess the applicants' ability and willingness to repay the loan employing a consistent and objective approach. Another important driver is the ability to make the application decisions quickly. With the increase in the number of lenders, applicants shopping for the best deal want to know quickly whether they will be granted a home loan, and on what terms and conditions. Thus, credit scoring reduces the time in loan processing process which would result in cost savings for the bank, which can be passed to the applicants in the shape of more favourable terms and conditions. Finally, credit scoring also helps lenders to take a balanced approach to risk management; thereby producing decisions which are transparent and consistent in terms of reporting, governance and control.

2.10.3 Home Loan in the Nepalese banking sector:

The market for residential facilities has witness an upward trend from the year 2002 with the shift in the lending paradigm for Nepalese banks to consumer credit. Home loan constitute about 80% of the total consumer credit in the Nepalese banking sector (Sherchan and Lamsal, 2005). Table 2.16 shows the amount of home loans disbursements made by major class "A" Nepalese commercial banks from the period 2002-2005.

Table 2.16 Home Loans Disbursements for the period 2002-2005 by Nepalese banks:

(Nepalese Rupees in Millions)

Name of the Bank	2002-03	2003-2004	2004-2005
Laxmi Bank Limited	23	79	149
NIC Bank Limited	-	-	130
NB Bank Limited	-	-	104
NABIL Bank Limited	36	141	321
Nepal Bank Limited	-	-	50
Bank of Kathmandu Limited	-	80	183
Rastriya Banijya Bank Limited	-	-	70
Everest Bank Limited	349	688	925
Standard Chartered Bank Limited	317	356	460
Machapuchhre Bank Limited	-	-	100
Kumari Bank Limited	200	300	400
Nepal Investment Bank Limited	41	61	74
Nepal SBI Bank Limited	26	177	443

(Source: Sherchan and Lamsal, 2005, Housing Growth: Is it for real? New Business Age)

The home loans are disbursed for the purchase of a plot of land; for the purchase of a plot of land and construct a house on it; for the purchase of already built house; for the purchase of flats or apartments or bungalows constructed by builders/developers;

for the construction of house on land already owned and for renovation, modification, extension of existing house. The main features of home loans in the Nepalese banking sector, which is distinct in the consumer credit sector are presented in Table 2.17:

Table 2.17: Features of Home Loan in the Nepalese Banking Sector:

Features	Descriptions
Eligibility	Applicant should be a Nepalese Citizen, below 60yrs of age holding permanent employment or self-employed with a gross monthly income of at least two times the monthly instalment of the loan amount.
Loan Amount	Ranges from Nepalese Rupees 5, 00,000 (approx. £5000) to 25, 00,000 (approx. £25,000). However, depending on the bank might be able to secure higher amount of loan subject to bank's personal decision.
Borrower's Equity	Ranges from 20-30 percent of the property value.
Security	The property is secured as collateral for the loan. Also personal guarantee of person(s) acceptable to the bank is obtained.
Disbursement of the loan	For the outright purchase of house or flat, the home loan will be paid in lump sum to the seller at the time of registration after satisfying that the borrower has paid his contribution. However, for construction of house/flat, the home loan would be disbursed depending upon the progress of construction after ensuring that the borrower has invested his equity contribution.
Payment Period	The payment period ranges from 5-25 years which is on an EMI (Equated Monthly Instalment) basis.
Property Insurance	The borrowers have to ensure that the property is fully insured against fire, riots and other hazards as required by the bank.

(Source: Compiled from the Websites of Nepalese Banks)

In addition to the above features, banks may levy a loan processing fee, a prepayment charge, a penal interest (in case of default) and the right to recall the full outstanding loan in case of continuous default of three monthly instalments. Nepalese banks have been making home loan decisions based upon the subjective evaluation of the prospective borrowers (Ramamurthy, 2004). The decision to grant a home loan is also influenced by the borrower's reputation or the social status and the book value of the underlying collateral, which places a question on the lack of objectivity in decision making (The Himalayan Times, 2008). However, borrower's equity of up to 20-30 percent of the value of the property is required for most of the home loans granted by Nepalese banks as directed by the policy of the Nepal Rastra Bank (Sherchan and Lamsal, 2005). Though, the rate of defaults is low in consumer credit especially home loans due to the high percentage of borrower's equity and the loan are disbursed depending upon the stage of construction of the house. From the literature there are clear issues faced by Nepalese banks as they move towards the adoption of the risk based approach on credit decision making in line with the Basel II guidelines. These have been summarised by Ramamurthy (2004) as:

1. The loan originating decision is based on subjective or judgmental evaluation of the credit application forms.

2. Processing of loan applications is time-consuming and has to pass through a hierarchy of lending authorities within the bank.

3. The lack of customer risk rating models makes loan pricing and risk management difficult.

4. Lack of centralised database to track historic, current as well as rejected applicants.

5. At times, the price of the property and construction are inflated by consumers to get additional finance.

In order to assist Nepalese banks to maintain the best credit risk management practices, the Credit Information Bureau (CIB) was set up in 1989 under the Nepalese Banker's Association (NBA). However, CIB was registered as a company in 2004 and started its operation from March 2005. In 2008, CIB changed its name to CIC (Credit Information Centre). At present, CIC is mainly involved in providing the database of blacklisted borrowers only as they are not ready technically with a mature database to provide credit bureau information to the Nepalese banking sector.

According to the Nepal Rastra Bank Act (2002) it is mandatory for commercial banks and financial institutions to submit reports on all newly issued loans with an exposure in excess of NRs. 1 million (approx. £10,000) at the end of each month. Prior to granting a loan of NRs. 500,000 (approx. £5,000) or more, banks are required to obtain a credit report. With regard to home loans, it is mandatory for all Nepalese banks and financial institutions to obtain a credit report from CIC before the loan has been disbursed. The CIC only provides information if the prospective borrower is in the blacklisted list. However, from the credit risk management perspective, it would be ideal if a comprehensive report on the prospective borrowers' creditworthiness is obtained from the CIC. Further, for a prudent risk management in all the loans and advances, Nepal Rastra Bank have made it mandatory for Nepalese banks to classify its loans and make provisioning on funded outstanding (Nepal Rastra Bank, 2004) as per the criterion presented in Table 2.18.

Table 2.18: Loan classification and Provisioning on Funded Outstanding:

Loan Classification	Criteria	Required Provision
Standard	Performing	1%
Sub-standard	Past due 3+ to 6 months	25%
Doubtful	Past due 6+ to 12 months	50%
Loss	Past due above 12 months	100%

(Source: Nepal Rastra Bank, Loans and Advances Directives, 2004)

In the Forum on Asian Insolvency Reform (2004), Ramamurthy reports that the credit risk management within the Nepalese banking sector are impacted by a plethora of factors. In particular these are lack of transparency while reporting financial statement by the loan seekers; existence of multiple banking by the loan seekers leading to diversion of funds, capital flight and over financing. This is being compounded by the lack of proper customer risk rating models and non-existent of credit rating agencies. Also, information on customers is not shared among the banks and financial institutions within the Nepalese banking sector. Thus, the prime challenge for Nepalese banks is to develop customer risk rating models based on statistical techniques so that the credit decision is objective, fast and consistent and the regulatory requirements for a risk based supervision as discussed in Chapter One could be adhere to.

2.11 Chapter Summary:

This chapter has reviewed the existing literature on credit scoring and its importance in the consumer credit industry. The sections on the judgmental lending and consumer credit provided an in depth understanding on how the credit decision making process have evolved over the years from the subjective to an objective approach on the lines of credit scoring. Thereafter, the current literature on credit scoring with the determinants of the predictive power of credit scoring models in terms of account definition, characteristics or variables selection, time horizon, sample selection and the importance of reject inference were discussed. Subsequently, an overview of the different statistical techniques used to develop credit scoring models in consumer credit with a discussion on the most appropriate technique were presented. Modelling issues such as model overrides, model validation and performance were consequently discussed. Thereafter, the conceptual framework of the research which is built on home loans were presented with a discussion on home loans, home loan default, home loan risk, theories relating to the risk of default. Finally, the importance and use of credit scoring for home loans with emphasis on the Nepalese banking sector were discussed.

Chapter 3: Research Methods

3.1 Introduction:

The purpose of this chapter is to explain and substantiate the research methods used in this study. After reviewing the literatures on credit scoring in the previous chapter, the research gaps have been identified which have enabled the formulation of the main and sub-research questions that underpin this thesis. Subsequently, a short discussion justifying the choice of the appropriate philosophical paradigm adopted for this research is presented. Thereafter, the mixed method approach involving questionnaire survey, expert interviews and credit application forms which were used to collect the data are presented. Further, a discussion on the sampling choice and the administration of the data collection process followed by the method of analysis are presented. Furthermore, it is imperative to establish that the research methods are appropriate in terms of its validity and reliability which are presented thereafter. Finally, the strengths and limitations of the mixed methods research together with the ethical considerations are presented.

3.2 The Research Gaps:

The Asian Banking Sector in general and the Nepalese banks in particular have witnessed considerable shift in recent years (2002 onwards) in their business generation in favour of their credit portfolio (New Business Age, 2005) with a resultant focus on consumer credit. The consumer credit decision process in Nepalese banks has traditionally been based on judgmental evaluation and financial analysis (Ramamurthy, 2004; Upadhyay, 2005). However, with the growth of the consumer credit portfolio and the increased emphasis placed on risk management (Nepal Rastra Bank, 2004) in the Nepalese banking sector, an objective consumer credit risk assessment framework is becoming increasingly essential to replace or complement the present system (Nepal Rastra Bank, 2004).

As already discussed within the consumer credit risk literature, academics and lenders have developed sophisticated statistical tools (credit scoring) to objectively assess consumer credit risk (Reichart *et al.,* 1983; Hand and Henley, 1997; Thomas, 2000; Crook *et al.,* 2007). There is also evidence within the literature of the wider use of credit scoring for credit classification, decision and forecasting purposes (Rosenberg and Gleit, 1994; Hand and Henley, 1997; Thomas, 1998, 2000; Anderson, 2007).

Banks in the UK and US have been using credit scoring to reduce their credit defaults, improve process efficiencies and credit approval time and move towards an objective, consistent method of credit decision making. However, the literature is sparse on the development and application of the statistical approaches already discussed for consumer credit in the Nepalese banking sector (Ramamurthy, 2004; Upadhyay, 2005; Nepal Rastra Bank, 2004). Thus, this research aims to address the gaps by carrying out an empirical study to develop a credit scoring model which would address objectivity as well as risk management for application within the Nepalese banking sector.

3.3 The Research Questions:

The main research question is:

"To what extent is the development of an objective credit scoring models achievable within the Nepalese banking sector"

The following sub-questions would assist the researcher towards finding the appropriate answer to the main research question above. The sub-questions are as follows:

1. What is the best method/way to evaluate the creditworthiness of the applicants?
2. What are the factors/characteristics that lenders should consider while assessing an application for consumer credit?
3. What are the issues to be considered while developing and implementing the credit scoring models within new or emerging markets?

3.4 Appropriate Philosophical Paradigm:

According to the positivist school of thought (Crotty, 1998; Easterby-Smith *et al.*, 2002; Saunders *et al.*, 2005), risk research is represented as the study of "objective" risk and attention has been devoted mainly to the development of models and methods to measure and manage it (Ciancanelli *et al.*, 2001). In this research context, the main research question is to investigate whether the development of an objective credit scoring models is achievable within the Nepalese banking sector. The credit scoring model derived as a result of the research should be:

1. *Objective:* the objectivity is derived from the use of quantitative methods (statistical techniques) to develop the model.
2. *Consistent:* the credit decision would be consistent at all levels through the use of the derived model. Risk exposure levels would be maintained and applicants would be treated equally irrespective of the channel by which they apply for credit.
3. *Empirically derived:* the data to building the credit scoring model is collected from the existing credit application forms of a Nepalese bank.

With a positivistic form of enquiry, the empirical data would be examined logically in order to develop a credit scoring model which would be objective, consistent and empirically derived. However, the deductive theory testing proposition of the positivist paradigm often does not adequately address and capture softer issues. These softer issues are related to the current credit decision making process, data handling and capture, characteristics selection, model development, model implementation, model performance and evaluation which needs to be accorded due consideration because it enriches the research process. As argued in the literature reviews presented earlier the theory relating to credit scoring is established. However, the theory relating to the application of credit scoring and the determination of characteristics is naive in the Nepalese banking sector, so theory development should be incorporated at this stage of the research. Henceforth, positivist paradigm on its own is not adequate to address these research issues.

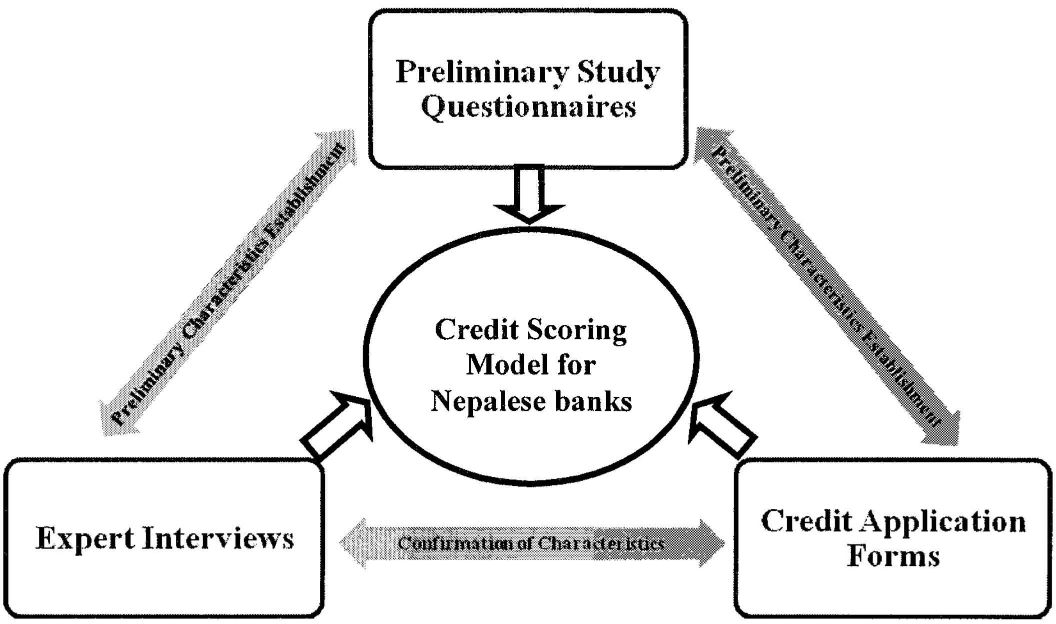
Since credit scoring was not adopted in the Nepalese banking sector for credit decision making, so before the credit scoring model development process it was necessary to address the softer issues relating to the current credit decision making process, the identification of characteristics, data handling and capture, model development, model implementation, model performance and evaluation from the managerial perspective. Henceforth, it was at the essence of this research to conduct an expert interview with those closely involved (credit officers) in the credit decision making process to get their views. These views were often subjective in nature which results from the interpretation an individual has placed on the events. Through the administration of expert interviews with the credit officers, theory could be generated and these softer issues could be explored with rigour. Though theory generation is part of the research process, the interpretivist paradigm on its own is unsuitable for this research.

Thus, by combining the benefits of the positivist and the interpretivist paradigms, this research would be able to address the research questions judiciously. Philosophically, the philosophy of "Pragmatism" is adopted in which both the quantitative and qualitative methods are compatible (Howe, 1988). Further discussions on the philosophical paradigms are presented in Appendix A.

3.5 Mixed Methods Research Design:

A sequential mixed methods comprising of the preliminary study questionnaire survey, an expert interviews and the credit application forms has been employed in this research. Detailed discussions on each of these methods are presented in Figure 3.1.

Figure 3.1: Mixed Methods Research Design:



(Source: Developed for this research)

3.5.1 Preliminary Study:

Questionnaire is the most commonly used method of data collection in survey research whenever large populations need to be studied (Stone, 1978). In a questionnaire the respondents are asked the same set of questions in a pre-determined order (deVaus, 2002) and the respondents answering the questions actually record their own answers (Kervin, 1999). Questionnaire also provides a quick and efficient way of gathering data at relatively low cost and less time in comparison with other data collecting methods (Newman, 2006; Saunders *et al.*, 2005). Jankowicz (2005) noted that *"questionnaire, if worded correctly, normally require less skill and sensitivity to administer than semi-structured or in-depth interviews"*. Moreover, when the fixed response questionnaire is employed, interviewer biases are also eliminated (Neuman, 2006).

In the preliminary study, questionnaire was administered as part of the Advanced Business Research Methods (ABRM) project undertaken during the taught stage of DBA programme. The main objective of the questionnaire survey was to get an initial overview on consumer credit risk and to establish the characteristics considered to be important in assessing the applicant for credit from the non-managerial staff (credit assistants and credit supervisors) working in the Nepalese banking sector. In accordance with the research design, the findings from the preliminary study would inform the expert interviews and the credit application form data collection process.

The non-managerial credit staff was chosen as respondents for the preliminary study because they were responsible for making the credit proposal or credit report based upon the application forms and other documents submitted by the prospective applicants. These credit staff are important because based on their credit appraisal; the credit officer/manager would make a decision whether or not to grant credit. The questionnaire survey was chosen as the appropriate method for the preliminary study because a large number of respondents could be contacted within a relatively short period of time adding to cost efficiency and it also fitted perfectly with the research design. Usually there exists a large population of non-managerial credit staff and through the administration of questionnaire survey a sizeable sample size could be accessed easily.

3.5.1.1 Questionnaire Design:

Before designing the questionnaire, hard copies of the home loan application forms from 17 Class 'A' Nepalese commercial banks were collected. Thereafter, with reference to the literature reviews, the application forms were thoroughly examined to identify the type of information (variables or characteristics) the banks ask from the applicants. Burns and Bush (2000) suggested five 'shoulds' of question wording when developing questions. These are the questions should be focused on a single topic, brief, easily interpretable by all respondents in the same way, use the respondent's core vocabulary and grammatically simple. Adopting the Burns and Bush (2000) principles, the questions were developed, focused on the objective of the study, being brief, with the same set of questions for all respondents, in the English language with simple sentences divided under two sections (Questionnaire attached in Appendix B2). Section A questions related to the consumer credit risk which included questions on the consumer credit policy, banking culture, credit decisions, risk profiling, existence of risk management department, and use of the credit information bureaus.

Section B contained the questions related to the characteristics or variables used in assessing the creditworthiness of the applicant for home loans. From the application forms thirteen characteristics relating to applicant age, number of dependents, marital status, employment status, years of employment, monthly expenditure, loan-to-value ratio, collateral/guarantee, property value, loans defaulted, total assets, property location and monthly income were identified. These characteristics were scaled into a five-point likert scale using a standard set of responses which were - very important, important, moderately important, of little importance and unimportant. In this technique, the respondents were asked to indicate the importance they attach to the characteristics which they consider important while assessing the application forms for preparation of the credit proposal or credit report for further credit decision making by the credit officer/manager. Additionally, a covering letter was attached to the questionnaire citing the purpose of the study, ethical issues on the treatment of the data and instructions on how to answer the questions.

3.5.1.2 Sampling Choice and Administration of the Questionnaires:

A random sample choice of 126 respondents were drawn from a population of about 400 non-managerial credit staff working in the Kathmandu Valley branches of the 17 Class 'A' Nepalese commercial banks. The choice of the non-managerial staff was based upon the following considerations:

1. They formed the first and direct interface with the customer and deal with initial queries and application forms.
2. Based upon the application forms submitted, they conduct a preliminary study and prepare the credit proposal or credit report which is then forwarded to the credit officer/manager for the credit decision making process.

3. Since they represent the first line in the interface with the customer, their views and opinions would be valuable for the conduct of the preliminary study in the research.

The questionnaires were delivered personally to each respondent and collected later through the help of the researcher's colleagues working in the Nepalese banking sector. The researcher ensured that questionnaires pack were printed and positioned in the right order. As the researcher was not involved with the distribution and collection of the questionnaires, the whole process took about three months and through regular follow-ups, a final response of seventy two (72) questionnaires were received back, which accounted for a fifty seven (57) per cent response rate.

3.5.1.3 Method of Questionnaires Analysis:

Section A of the questionnaire related to the current consumer credit management was analysed using descriptive statistics. Since the answers to the questions were defined into categories ("yes" or "no"), the frequencies were used to find out the number of respondents in each category. Thereafter, for the section B questions which relates to the characteristics considered important to assess the creditworthiness of the applicants for home loans, an exploratory factor analysis was used. According to Pallant (2007, p. 179) *"factor analysis can be used to reduce a large number of related variables to a more manageable number, prior to using them in other analyses such as logistic regression".* From the range of thirteen characteristics, for the ease of determining which characteristics were most important and could be considered in the credit scoring model to be developed later in the research process, it was necessary to reduce the large number of characteristics to a manageable few characteristics.

In this process, exploratory factor analysis in the form of principal component analysis (PCA) with varimax was used to reduce the number of characteristics. Within the literature, Anderson (2007) has advocated the use of exploratory factor analysis for credit scoring models where data reductions in the number of characteristics are being considered. Sidiqqi (2005) has used principal component analysis in order to identify group of correlated variables while developing the credit scorecards. It is used in credit scoring as part of the variables selection process (Mays, 2004; Sidiqqi, 2005; Anderson, 2007).

In predictive modelling, exploratory factor analysis is being used by credit scoring model developers to choose one or two of the underlying characteristics to represent each factor (Mays, 2004). The preliminary study relates to ascertaining and reducing the number of characteristics to be considered in the credit scoring model. In this process exploratory factor analysis is considered appropriate to be used in the early stages of the research to explore the interrelationships among the characteristics or variables to be considered in the model development process (Pallant, 2007).

3.5.2 Expert Interviews:

At the most basic level, "*interviews are conversations, whose purpose is to obtain descriptions of the life world of the interviewee with respect to interpreting the meaning of the described phenomena*" (Kvale, 1996 p.5). As such they have the capacity to gather opinions, identify issues and explore the situation (Carroll and Johnson, 1990). Interviews involve meetings between the interviewee and the researcher for the purpose of elucidating and elaborating upon the themes that emerged from the literature reviews, preliminary study and for noting any contradictory data (Creswell, 2003). Kvale (1996) viewed that though interviews promote understanding and change; the emphasis is on intellectual understanding rather than on producing personal change.

Patton (1990) identifies four types of interview method:

1. ***The Informal Conversational Interview***: These are interviews that occur spontaneously in the course of field work and the respondent may not know that an interview is taking place. These interviews are highly individualised and the questions emerge from the immediate context. The interviewer should be knowledgeable, experienced and have a strong interpersonal skills. Since this type of interview is widespread, the data analysing might be difficult and time-consuming.
2. ***The Interview Schedule Approach:*** In this type of interview, the interviewer has an outline of the issues to be covered; however a laissez-faire approach is adopted to conduct the interview in terms of wording and order of the questions. Though the data is systematic and comprehensive, the tone of the interview is fairly informal.
3. ***Standardised Open-ended Interview***: In this type of interview the questions are structured, with no flexibility in the order or wording of questions, although the responses are open-ended. If the audience is specialised and limited in number then this type of interview offers the best choice in terms of the issues to be explored in limited time. It also ensures that the same general areas of information are collected from each interviewee, thus providing more focus and adaptability in exploring and analysing information.
4. ***Closed, Fixed-Response Interview***: These are structured interviews in which the respondents are asked to choose from a predetermined set of response categories. The aim is that all the respondents receive the same questions which are very

specific with a fixed range of answers. Though the data can be coded and analysed easily, this type of interview does not bring about the essence of interviews which are conversations according to Kvale (1996). So it does not bring about the personal views of the interviewees on the issues explored.

The primary purpose of the expert interviews is to explore the meanings interviewees attach to issues and situations in the context of the research (Easterby-Smith *et al.*, 2002; Flick, 2006). The importance of the interview is summarised by Burgess (1982, p.107), *"(the interview) is ... the opportunity for the researcher to probe deeply to uncover new clues, open up new dimensions of a problem and to secure vivid, accurate inclusive accounts that are based on personal experience."* Kvale (1996, p.65), stresses the objectivity of qualitative interviews by saying that *"qualitative interviews can approach objectivity in an arithmetic sense of intersubjectivity when following similar procedures in a common interview guide, come up with closely similar interviews from their subjects"*. This view of Kvale is supplemented by Easterby-Smith *et al.*, (2002, p.86) by adding that *"a positivistic approach can be retained where the interview follows a fairly standardised set of questions, whilst offering some flexibility, and allowing the views of the interviewee to become known."*

To answer the research questions, it is essential to understand the current consumer credit decision making process in the Nepalese banking sector. Additionally, there is a need to explore the softer issues relating to selection of characteristics or variables, data handling and capture, model development, model implementation, model performance and evaluation from the managerial perspective who are closely associated with the credit decision process, which would enhance and enrich the research process.

Moreover, the interview process would enable the researcher to confirm the characteristics or variables which were established during the preliminary study for the purpose of developing the credit scoring model. Thus, in order to understand and explore these issues, there is a need to invite those closely associated with these issues for a conversation, thus providing a rationale for conducting the expert interviews.

<u>3.5.2.1 Expert Interview Guide Design:</u>

According to Kvale (1996, p.65), an interview can approach objectivity *"if it is unbiased, follows similar procedures using a common interview guide and reflect the real nature of the object studied."* Maintaining this view and the research objective, the standardised open-ended interview using an expert interview guide was chosen as the most appropriate interview method as it is characterised by a systematic form of questioning contributing to knowledge production and also promoting a good interaction (Silverman, 2001). The expert interview guide were developed taking into consideration the literature reviews, the research gaps and its rationale. The expert interview guide would have a detailed sequence of topics with its related questions which would contribute to the research process.

However, to confirm the appropriateness of the interview guide in terms of the topics and its related questions, it was necessary to pilot them (deVaus, 2002). Piloting helps to check whether the interviews are going to function effectively, to check that the questions are not ambiguous and to restructure questions so as to obtain richer data (Baker, 1994).

deVaus (2002, p.54) said *"Do not take the risk. Pilot test first"*. Since the interviews were targeted at the credit officer of Nepalese commercial banks, it could be argued that the piloting be done with similar interviewees to ensure that the interviewees have no problem with understanding and answering the questions. Thus, to pilot the expert interview guide, the researcher approached a well established UK bank during October 2006. After presentation of the purpose of the research and also the pilot study, two Senior Officers from the UK Bank who had practical experience of over 20 years in the field of consumer credit and credit scoring agreed to take part in the piloting process. The pilot process was conducted in their office premises towards the end of November 2006.

Before the piloting process, the expert interview guide was sent out, so that the experts were able to read and thus make appropriate comments. To align with the issues raised in the literature reviews, these expert helped reframe the questions. Thus, the piloting process was able to take into consideration the expert's views supported by the literature and helped the researcher to redesign the expert interview guide.

The major areas covered in the expert interviews were the credit decision process, data handling and analysis, model development, model implementation issues, model evaluation and performance issues. A full list of the pre and post piloted questions (attached in Appendix C4) and the final expert interview guide (attached in Appendix C2) are presented. An example of the improvement in the expert interview guide as a result of the piloting process is shown in Table 3.1.

Table 3.1: Example of the Improvement in the Expert Interview Guide

Examples of Questions before piloting	Examples of Questions after piloting
Will you describe the retail credit decision process within your bank?	How would you describe the current consumer credit decision process within your bank?
Will the overrides data be analysed and built back into the model?	If there were any overrides in the credit decision process, would the overrides data be analysed and built back into the model? If so, how?
To what extent, if any, will your bank evaluate any credit scoring model against qualitative risk?	Is your bank likely to adopt a combination of judgmental/quantitative approaches to credit scoring?

(Source: Compiled for this research)

3.5.2.2 Sampling Choice and Administration of the Expert Interviews:

According to Burns and Bush (2000) sampling involves taking a portion of the population, making observations on the smaller group and then generalising the findings to the large population. However, Flick (1998, p.41) viewed that *"it is the relevance of the research topic rather than the representativeness which determine the way in which the people to be studies are selected"*. Considering Flick's view, the sampling choice for conducting the interviews are the credit officers in the Nepalese banking sector. In terms of the sampling frame, Neuman (2006) noted that when the objective is to collect unique cases that are especially informative and specialised, then we should use purposive sampling. In the context of this research, the interviewees are the credit officers who are informative in their specialised population- the banks, so purposive sampling is adopted to conduct the expert interviews.

After piloting the expert interview guide with the senior officers in the UK banks, it was possible to conduct the main interviews. Telephone calls and emails with a request to participate in the interview process were sent to the credit officers of eight Nepalese commercial banks. These banks were selected because they had participated in the first Quantitative Impact Study (QIS) of the Basel Accord Implementation Group set up by the Nepal Rastra Bank's Banking Supervision Department (Nepal Rastra Bank, 2005). Out of the eight banks, credit officers of five banks responded and agreed to participate in the expert interview process. Thereafter, the expert interview pack which contained an introduction letter (attached in Appendix C1) explained the purpose and the nature of the study; the expert interview guide(attached in Appendix C2) and the informed consent form (attached in Appendix C3) were sent. Subsequently, the interviewer made travel plans to visit Kathmandu during the first week of January 2007 to conduct the interviews. The interviews were held at the premises of the five banks, however due to the sensitive nature of information related to the banking sector, the participant banks were identified as bank A, B, C, D and E and the responses were recorded manually in the expert interview guide.

3.5.2.3 Method of Expert Interviews Analysis:

The objective of expert interviews data analysis is to identify, examine, compare and interpret patterns and themes (Hair *et al.,* 2007). Flick (2006, p. 165) advocates that *"the interpretation of expert interviews mainly aims at analysing and comparing the content of the expert knowledge".* Interviews data analysis is also determined by the nature and the quantity of the data gathered. In this research, since the expert interview data were limited (five interviews recorded manually), the author would focus in extracting meanings from the responses by highlighting the main themes and arguments presented, so as to generate theory relating to the current consumer credit decision process and the credit scoring modelling process within the Nepalese banking sector. One of the popular interview data analysis technique formulated by Miles and Huberman (1994) known as matrix analysis could be used for limited interviews data in order to identify themes and arguments.

Matrix analysis involves *"the crossing of two or more dimensions or variables to see how they interact"* (Miles and Huberman, 1994, p. 239). In a matrix format, *"the set of responses are arranged in rows or columns"* (Agnes, 2000, p.887) so that themes could be generated from the data. In Table 3.2 the use of matrix analysis to analyse interview data by previous studies are presented.

Table 3.2: Applications of Matrix Analysis

Study	Data Collection Methods	How Matrix Analysis was used
Maxwell (1996)	Interviews	Data-planning matrix to display a set of research questions along the vertical axis, with a set of evaluative questions along the horizontal axis.
Schensul *et al.*, (1999)	Ethnographic Data	Display specific research tasks along the vertical axis with a set of key parameters along the horizontal axis.
Marsh (1990)	Semi-Structured Interviews	Process-oriented matrix to study the impact of healthy lifestyle changes in adults.
Sandelowski (2000)	Interviews and Questionnaires	Designed matrix as a visual worksheet for blending qualitative and quantitative research based phenomena.
Straub and Welke (1998)	Interviews and Action Research	Designed countermeasure matrix model to analyse systems risk.

(Source: Compiled for this research)

While analysing the semi-structured interviews to study the impact of healthy lifestyle on adults, Marsh (1990) concluded that matrix analysis has worked as an ancillary strategy in assessing the trustworthiness of a qualitative study. By using a matrix display, one can graph the known intersections between dimensions of phenomena, providing an expansive picture of the researcher's focus area (Morse and Field, 1995). Descriptive matrices allow the researcher to display categorised data in individual cells, just to observe what appears which reflect paraphrased, synthesised or quoted content from participant responses (Marsh, 1990; Miles and Huberman, 1994).Thus, in line with previous studies, this research would adopt matrix analysis to analyse the expert interview data in this research.

3.5.3 Credit Application Forms:

In the preliminary study as well as the expert interviews, the characteristics which were considered important in assessing the creditworthiness of the customers were identified. These characteristics related to the demographic, financial, employment and behavioural information of the customers. Thomas *et al.,* (2002, p. 23) argued that *"the art of scoring is related in deciding which characteristics to keep and which to ignore".* However, in developing a bespoke credit scoring model for the first time it is imperative to consider all the characteristics from the credit application forms and establish which is more significant from the statistical perspective rather than consider the characteristics identified through the subjective approach (MacNeill, 2000). The primary interest being to determine the correlation of the characteristics and to ensure that the characteristic which is statistically significant is adapted in the model.

As discussed within the literature, the credit scoring model building process takes into consideration the historical customer data which is obtained from the credit application forms. In the Nepalese banking sector, where there is no history of formal credit scoring, one of the major challenge is to extract the historical customer information that have been granted credit. This information is stored in the form of hard copy credit files and a challenge for the researcher was to capture the information in the electronic format which could be readily used for modelling purposes. In order to use data from customer forms it is necessary to ensure firstly that the credit application form data has to be from a single time period. This common time period offers the benefits of ensuring that all applicants were subject to the same conditions, both at the time of application and during the time of the loan. Additionally, the applications were subject to the same application and management procedures during these times. Secondly, the data has to be from a population applying for a specific credit product. For example, data obtained from the home loans would give a better homogeneity with the policies and decision criteria applied. (MacNeill, 2000).

One of the important issues surrounding all credit scoring techniques is the relationship between the sample size used for developing the model and the predictive performance of the final model. According to Lewis (1992), the predictive performance of the credit scoring model depends upon the sample size and the nature of the data on which the model is built. Generally, the larger the sample, the better the model. This is due to the fact that increased sample size provides better representation of the population thereby enhancing the model prediction accuracy. However, the literature is sparse about the relationship between sample size and the model's predictive performance (Hand and Henley, 1997; Thomas, 2000) and there is no precise recommendation of what constitutes an acceptable sample size in credit scoring (Finlay, 2006). Lewis (1992) suggested 1500 good and 1500 bad cases; Siddiqi (2005) suggests 2000 samples in each class. The sample sizes used in various studies for developing credit scoring models are presented in Table 3.3 for reference and comparison. Further, none of these studies provided any empirical evidence to support as to what the optimal sample size should be or more important the consequences of the larger or smaller sample on the model output and its reliability. Thomas *et al.,* (2002) recommends using full population in small portfolios rather than sampling from it. Thus, it is imperative from the modelling perspective to understand the importance of the sample size for the model's predictive accuracy.

Table 3.3: Sample Size Comparison

Study	**Modelling Techniques Used**	**Sample Size Used**
Boyle *et al.,* (1992)	Discriminant Analysis, Decision Trees.	139
Henley (1995)	Discriminant Analysis ,Logistic Regression, Decision Trees.	4132
Desai *et al.,*(1997)	Discriminant Analysis, Logistic Regression, Neural Networks.	293
Arminger *et al.,* (1997)	Logistic Regression, Neural Networks.	1294
West (2000)	Discriminant Analysis, Logistic Regression, Neural Networks, Decision Trees.	270; 345
Baesens *et al.,* (2003)	Discriminant Analysis, Logistic Regression, Neural Networks, Decision Trees.	200; 264; 1438
Malhotra and Malhotra (2003)	Discriminant Analysis, Neural Networks.	1078
Abdou *et al.,* (2007)	Logistic Regression, Neural Networks.	581

(Source: Compiled for this research)

Within the literature, it has been argued that credit scoring models developed only on the basis of the accepted applications is biased (Thomas, 1998; Banasik and Crook, 2007; Wu and Hand, 2007). This bias could have a major implication on the model performance as it does not take into consideration the applicants who were rejected. In order to reduce such bias, rejected customer data should be maintained and incorporated in the model development process. Thus, the final model would have both the observed (accepted applicants) as well as unobserved (rejected applicants) customer data which would make the model robust and reliable. The different reject inference techniques have been presented within the literature review in section 2.7.4.

Thus, from the sampling perspective, the main challenges in building a credit scoring model in a new market such as the Nepalese banking sector are the sample size and data on rejected applicants. As consumer credit market is in its infancy in the Nepalese banking sector, large samples were not available to be incorporated for model building. It is also important to note that within the Nepalese banking sector, there is no empirical evidence to suggest the rejected application was being maintained as part of the customer database management system and thus samples on rejected applications could not be used for model development. Thus, the model obtained as a result of this research might have potential bias of the sample size as well as reject inference which might result in potential effect on findings as the final model would not be able to perform as it would be expected to forecast the good and bad applications. Hence, for any future model development process in such market, it is suggested as part of the conclusion to this thesis is to build credit scoring model on larger datasets with reject inference being incorporated.

3.5.3.1 Sampling Choice and Administration Process:

The credit application forms data were collected from one of the Nepalese banks which had participated in the preliminary study questionnaires as well as the expert interview process. Necessary approval was obtained from the senior management of the Nepalese bank before the data collection process. The data were not stored in a computer generated program or excel files, so the research had to physically record the data from the individual credit files of the applicant and compile them in excel files. It is imperative from the literature that for the model development purpose, the credit application forms data has to be from the same time period and specific credit product.

Moreover, as recommended by Thomas (2002) a full population of two hundred and two (202) home loan credit application forms data for the period of one year (2005-2006) were collected from the Nepalese bank. Furthermore, the data was collected after a time horizon of one year (during December 2007) as recommended by Bhatia (2006), both the borrower's characteristics as well as the default status could be observed.

3.5.3.2 Method of Model Development:

From the literature, it could be argued that logistic regression is the appropriate statistical technique to develop the credit scoring model for a new market which does not have history of credit scoring (Crook *et al.,* 2007). Logistic regression is also the technique of choice for this research because of it being statistically acceptable (Srinivasan and Kim, 1987; Henley, 1995; Sidiqqi, 2005; Crook *et al.,* 2007).

Logistic Regression (LR) assumes the existence of a dependent or continuous characteristics 'Y' which is defined as the probability that borrower into "good" or "bad" credit risk and can be modeled as a linear function of a set of independent characteristics 'X' (Sharma, 1996; Field, 2005; Tabachnick, and Fidell, 2006) which is expressed in Equation 3.1 as:

$$\mathbf{Y = \alpha + \beta_1X_1 + \beta_2X_2 + \ldots\ldots\ldots\ldots + \beta_nX_n} \qquad \textbf{(Equation 3.1)}$$

Where, α is the intercept term,

β_n is the coefficient of the n^{th} characteristics, and

X_n is the value of the characteristics n.

To select the characteristics to be included in the logistic regression Equation 3.1, backward selection method was used. In the backward selection process, all the characteristics are included in the model so that the significance of coefficients and overall significance are evaluated. The insignificant characteristics with 95% confidence level are thrown away, with the other characteristics the model is again constructed and the significance of the characteristics is checked and insignificant characteristics are again thrown away. This procedure is continued until the significant model with significant parameters is established. Logistic regression applies maximum likelihood estimation after transforming the dependent variable (Field, 2005; Pallant, 2007). Since, the dependent characteristics "Y" is unobservable, the probability of "Y" occurring given the values of the predictor (independent characteristics) is calculated as in Equation 3.2:

$$\mathbf{P(Y) = 1/\,(1+e^{-z})} \qquad \textbf{(Equation 3.2)}$$

Where $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots\dots\dots + \beta_n x_n$

Although the dependent characteristic takes values 0 and 1, the logistic regression equation does not give the prediction of 0 and 1. The logistic regression equation of linear combinations of independent characteristics gives the log odds, which would be transformed to the probabilities of default, which is then compared with the cut off value of 0.5 (the cut-off value is the value which maximises the model accuracy and in this model it is taken as 0.5). Thus, if the probability of default is less than 0.5 (50 per cent), then the applicant would be accepted and classified as good credit and if the probability of default is classified greater than 0.5 (50 per cent), then the applicant would be rejected as classified as bad credit.

3.6 Validity and Reliability of the Mixed Methods Research:

In business and management research, it is important to ensure validity and reliability of the research findings which can be achieved by emphasising the adequacy of the research methods and the quality of measurement procedures employed (Krausz and Miller, 1974; Selltiz *et al.,* 1976; Neuman, 2000; Bryman and Bell, 2007). In this process, the theoretical paradigm underpinning the research should be compatible with the research design adopted so as to clarify the research problem. Selltiz *et al.,* (1976) emphasised that the measurement procedure consists of the data collecting technique which allows producing reliable evidence that is relevant to answer the research questions. Though, a careful and systematic method to collect the data is important, there might be differences in the approaches to measurement. Bryman (1984) argues that the qualitative research is embedded into social constructions, whereas quantitative research provides a static account. However, qualitative measurement involves assigning labels to identify different groups of situations and behaviours, while quantitative measurement involves assigning different numbers to differentiate magnitudes of variable (Neuman, 2000). Thus, a mixed methods approach could stress the need to analyse different measures strengths and weaknesses in relation to measurement of a particular situation (Brewer and Hunter, 1989)

According to Bryman and Bell (2007, p.41) the *"integrity of the conclusions generated from the research"* as an important criterion for validity. However, Yin (1994) has listed four considerations to judge the quality of the research design. These are construct validity, internal validity, external validity and reliability. Construct validity refers to the development of adequate operational measures for the concepts being tested (Yin, 1994). Through the literature reviews in Chapter Two, this research have identified the gaps in the literature and thereby formulated the research questions. Subsequently, the data (operational measures) would be obtained by adopting both qualitative and quantitative methods. At the first instance, by employing questionnaire survey in the preliminary study, an initial overview on the credit decision process as well as the characteristics lenders consider in assessing the creditworthiness of the applicants are established. In line with this, the expert interviews conducted in the second phase through the qualitative approach complements the research process by providing insights into the credit decision making process and other issues related to the model development from the managerial perspective. Finally, the characteristics collected from the credit application forms are analysed using statistical techniques. Thus, the construct validity of the research is improved.

Bryman and Bell (2007) have advocated that internal validity is related with the development of the underlying relationships whereby certain elements are shown to influence other elements in the research. The main purpose of this research is to develop a credit scoring model for the Nepalese banking sector. However, in a new sector, such as Nepal which does not have the history of credit scoring it is essential to undertake an in-depth study before the model is developed to identify other issues which might complement the research process. The questionnaire survey and expert interviews provides the internal validity to the research by exploring issues relating to characteristics selection, data capture and handling, model development, model implementation and model performance and evaluation which should be considered before developing the model thereby increasing the credibility of the research outputs.

External validity refers to *"whether the results of the study can be generalised beyond the specific research context"* (Bryman and Bell, 2007, p.42). It is also concerned with the representativeness of the research samples (Tashakkori and Teddlie, 1998; Neuman, 2000). According to Tashakkori and Teddlie (1998, p. 63) *"the more representative the sample of individuals or events/situations are, the greater is the probability that research findings have external validity"*. The results from this research could be applied to the Nepalese banking sector as well as other new or emerging markets where the application of credit scoring is sparse.

Finally, reliability means consistency or dependability, which suggests that the same results are repeated or recur under identical or very similar conditions (Neuman, 2000). The reliability has be achieved by piloting the expert interviews guide with two senior officers from the UK banks and then using the final expert interviews guide with five credit officers from the Nepalese banking sector. Moreover, all the characteristics from the credit application forms have been considered in the model development process so that the final model would have those characteristics which are statistically significant and which add to the classification accuracy. By doing so, the reliability is enhanced. Thus, by adopting the mixed methods approach, the possibility of overlapping methodological biases will be minimised, thereby increasing the level of validity and reliability of research findings.

3.7 Strengths and Limitations of the Mixed Methods Research

The adoption of the mixed methods to inform this research has its own strengths and limitations. The main strength of this research process is that the author considers using both the qualitative and quantitative methods of data collection. The mixed method approach provided a rich context to the research process in terms of exploring the credit decision making process, identification of the creditworthiness characteristics, data capture, model development and model evaluation and implementation issues.

However, there are certain limitations which are of importance. Firstly, the questionnaire in the preliminary study was mainly designed to evaluate the characteristics used in credit assessment and did not cover a wide area of consumer credit management process. Secondly, though the expert interview guide was piloted with the senior officers of a UK bank, however certain areas related to credit scoring (for example: model development, model performance and evaluation) were new to the credit officers of the Nepalese banks which affected the non-availability of responses for certain questions. And finally, in comparison with prior studies on credit scoring modelling process as presented in Table 3.3, the sample size for this study were limited and were not available in a format which could be easily transferred for statistical analysis.

3.8 Ethical Considerations:

In business and management research, the importance of maintaining ethical standards arise at different stages of the research process which is driven by the data sources (Bryman and Bell, 2007; Saunders *et al.,* 2005). The ethical issues as summarised by Punch (2000) are privacy of the participants, informed consent, potential harm, deception and confidentiality of data. The ethical issues may frequently arise from a clash between personal and professional interests (Punch, 2000). In this research, the author has followed the ethical code and standards set by the University Ethics Committee at Northumbria University. The ethical concerns for this research are mainly focused on two areas: privacy of participants and confidentiality of data.

Privacy of the participants is a major ethical issue in business and management research (Bryman and Bell, 2007; Saunders *et al.,* 2005). In the preliminary study, this ethical issue was addressed by sending a letter along with the questionnaire to each respondent's explaining the purpose of the research and how the respondents' privacy would be protected (presented in Appendix B1). In the expert interviews, an introduction letter (presented in Appendix C1) along with the expert interviews guide and informed consent form are send to all the participants. The introduction letter explains the purpose of the research and participants' privacy protection. The informed consent form gives full information on the participation rights and use of the data (presented in Appendix C3). This ensures that the participant's right to anonymity is maintained through the research process. Further, the participating banks were assigned pseudonyms in the research process to maintained data secrecy.

For the credit application forms data, necessary approval was obtained from the senior management of a Nepalese bank which had participated in the expert interviews. Due to the sensitive nature of the data which has customer name, address and other financial details attached to it, pseudonyms were assigned to the bank. Further, to maintain anonymity, care was taken not to report customers' names or the bank involved while reporting the findings of the research.

Finally, necessary steps would be taken to minimise potential harm to the interview participants, the questionnaire respondents and the bank from where the secondary data were collected either in the research process or the findings, including the non-release of such data analysis into the public domain that would cause potential damage or harm.

3.9 Chapter Summary

To summarise, this chapter has identified the research gaps on which the research questions has been formulated. Thereafter, by combining the benefits of both the positivist and interpretivist paradigms, the author advocates for the pragmatism paradigm to underpin this research. Building upon the philosophical paradigm adopted for this research, a mixed method research design was presented. Then the data collection and analysis strategy in terms of preliminary study questionnaire, expert interviews and credit application forms were presented. The questionnaires were administered with the non-managerial staff of Nepalese banks so as to get an initial overview on the consumer credit risk and also to identify the characteristics which were used to assess the creditworthiness of the customers. The questionnaires were analysed using descriptive statistics and exploratory factor analysis. Thereafter, the expert interviews were conducted with the credit officers of the Nepalese banks so as to identify the softer issues relating to credit decision making process as well as the credit scoring models. The expert interviews were analysed through matrix analysis method. Thereafter, the credit application forms data for the model development process were collected from one of the Nepalese bank which had participated in the preliminary study as well as the expert interviews. The credit data were analysed to develop the model using logistic regression method. Finally, validity and reliability, the strengths and limitations as well as the ethical considerations were discussed.

Chapter 4: Analysis and Discussion of Findings

4.1 Introduction:

From the literature review in Chapter Two, it could be suggested that the specific literature relating to the credit decision making process within the Nepalese banking sector is sparse. In order to achieve the aims of this research as discussed in Chapters One and Three, it was important to understand the credit decision making process both from managerial and non-managerial perspectives and also, to confirm the characteristics considered as a measure of creditworthiness before developing the credit scoring model. In order to achieve this, the research followed a mixed methods (triangulation) approach as described in Chapter Three for data collection and analysis in terms of the preliminary study questionnaires, the expert interviews and the credit application forms. The preliminary study questionnaires were analysed using descriptive statistics as well as exploratory factor analysis to obtain factor solution in terms of data reduction. The expert interviews data were analysed using matrix analysis and the findings were discussed in terms of the major themes which emerged from the expert knowledge. Finally, the data derived from the sample of credit application forms were modelled using logistic regression to identify the combination of coarse characteristics that distinguish between loan re-payees and loan defaulters from the Nepalese banking sector.

4.2 Preliminary Study:

The preliminary study questionnaire was administered as part of the Advanced Business Research Methods (ABRM) project undertaken by the researcher during taught component of the DBA programme. The main objective of these questionnaires was to develop an understanding of the consumer credit risk and also to establish the characteristics considered to be important in assessing the applicant for credit from the perspective of non-managerial staff (credit assistants and credit supervisors) working in the Nepalese banking sector. The questionnaire survey data collection process and method of analysis is discussed in Chapter Three. The analysis and findings of the preliminary study is presented in Sections 4.2.1 and 4.2.2 of this chapter:

4.2.1 Consumer Credit in the Nepalese banking sector:

In this section, the findings of the section A questions of the questionnaire survey (attached in Appendix A) are presented. The main areas discussed are the credit policies, lending hierarchy and authority, credit decisions making and credit risk management.

1. Does your bank have a Consumer Credit Policy?

From the literature, it can be inferred that banks establish a draft consumer credit policies which contains the guidelines, directives, objectives and principles of the consumer credit decision making process as well as the risk management framework within the bank. From the survey responses 65 per cent of the respondents said that their banks have a consumer credit policy and 35 per cent said that they have no consumer credit policy.

2. Is the Policy different from Corporate Credit Policy?

In banks and financial institutions credit is divided into two distinct areas: corporate credit and consumer credit. Corporate credit (or wholesale lending) refers to borrowing by business and industry such as project finance, overdrafts, revolving credits, working capital finance in which the value of the businesses are high and where the number of deals are small (Anderson, 2007). In contrast, consumer credit (or retail lending) refers to the borrowing by individuals to finance current expenditure on goods and services such as home loans (mortgages), auto loans, education loans, travel loans, personal loans in which the value of the business is low, but the number of transactions are high (Bhatia, 2006). Given the differences described above, the credit policy should be different in each case of lending given the nature of risk, the information availability, the value of the business and the profiles of the credit. Moreover, consumer lending is a new paradigm in the Nepalese banking sector which started in 2002 as established in Chapter One. From the responses of the survey, it was found that 58 per cent of the respondents have said that the consumer credit policy is not different from corporate credit policy. However, this contradicts our findings from the previous questions "Do your bank have a consumer credit policy?" in which 65 per cent of the respondents said that they have a consumer credit policy in place. From the credit risk management perspective, since both of these types of lending are different, it could be argued that their credit policy should be distinct. Such a distinction in the credit policy could be used to potentially market the lending properly and also to allocate resources and capital adequately as per the risk appetite of the bank.

3. Does the Policy define Hierarchy and Authority?

In the traditional nature of bank management, lending decisions were taken by staff that held *"lending mandates"* (MacNeill, 2000) and who were senior in authority and higher lending authority rose monotonically from bottom to top. According to Ramamurthy (2004), the credit policy in Nepalese banks defines the hierarchy and authority for all lending decisions. The initial survey indicated that 78 per cent of the respondents said that they have defined the hierarchy and authority for lending decisions placed within the credit policy documents. From the credit control point of view such an approach might be satisfactory, but from the risk management perspective, the decision which is based upon subjective approach might be inconsistent as the perception of risk differs with the personality of the credit officers (MacNeill, 2000).

4. Does the Banking culture determine the rate and means by which Credit Policy differs?

With regard to the banking culture, corporate credit places greater emphasis on relationship banking whereas in consumer credit the emphasis on transactional banking (Allen *et al.,* 2004). Further, it could be argued that beyond a financial relationship no other relationship is relevant in the lending context. As reported by Sherchan and Lamsal (2005), relationship banking has been in operation for consumer credit in the Nepalese banking sector since its inception in 2002. The survey of credit assistants and credit supervisors found that 63 per cent of the respondents said that the banking culture determined the rate and means by which the credit policy differs. Thus, it could be argued that with the growth of consumer credit, relationship banking would shift to transactional lending in the future.

5. Are the Credit Decisions based on the profitability profiles, rather than the risk profiles?

The profitability of the credit decisions may be derived from the profitability of the associated products, for example in the case of home loans, banks may sell associated products such as buildings insurance, home insurance, payment protection insurance, endowment policies and indemnity guarantees (New Business Age, 2005). However, all the respondents from the initial study disagreed that credit decisions were based on the profitability profiles. Thus, it could be inferred that the associated products of consumer credit have not as yet been developed in the Nepalese Banking system.

6. Do you price the credit according to the risk profile of the applicant?

The risk profile of the applicant determines the rate of interest charged for the credit (McNab and Wynn, 2000; Sidiqqi, 2005). The rate of interest (price) is almost always high for high risk borrowers and low for low risk borrowers as defined by the bank providing the credit. The survey of credit assistants and credit supervisors responses showed that none of the Nepalese banks price credit according to the risk profile of the applicant. This may be due to the lack of a formal risk rating methodologies and customer risk rating models within the Nepalese banking sector (Ramamurthy, 2004). Thus, it could be argued that through the development of a formal risk rating model, pricing of credit could be conducted according to the risk profile of the applicant.

7. Do you think that adequate collateral/guarantor minimises credit risk?

Home loans are secured in favour of the lender as the property underlying the loan forms the security. About 90 per cent of the respondents agreed that adequate collateral/guarantor minimises credit risk. The extent of collateral security required is linked with the risk rating of the consumer. The higher the risk category the greater should be the value of the collateral.

8. Does your bank have a risk management department?

Nepal Rastra Bank (2007) has emphasised the requirement for a risk based approach to lending and risk based supervision within the Nepalese banking sector. As a first step towards this, it is imperative to separate the credit marketing and credit control functions, both of which traditionally would be found in a credit department. From the preliminary study around 40 per cent of the respondents agreed that they have a risk management department within their banks. These indicate that Nepalese banks are creating risk management department within their organisation structure to formally adopt a risk based lending approach.

9. Have you been trained in the areas of risk management?

An important aspect of risk management is that the staff working in the credit department should be trained in the area of risk management and should know the bank's credit policy, credit directives, and regulator guidelines on credit. Further, they should fully understand the business model of the bank and the risk appetite the bank is adopting. From the survey of the credit assistants and credit supervisors around one in three of the respondents have said that they have been given risk management training. This could mean that a majority of the personnel working in the lending areas of Nepalese banks have not taken any formal risk management training, which could also trigger a suspicion on the large level of Non Performing Loans (NPL) and low level of capital adequacy ratio in the Nepalese banking sector, especially in the state-owned banks (presented earlier in Table 1.4 and 1.5).

10. Is credit information from Credit Information Bureau (CIB) a mandatory part of the Consumer Credit Decisions?

Within the literature review, the mandatory requirement within the Nepalese banking sector is to seek credit information about the borrower from the credit information bureau (CIB) which is now credit information centre (CIC) prior to the granting of a customer loan was identified (as presented in Chapter Two). From the responses in the preliminary survey, the respondents agreed that the credit report is mandatory as part of the consumer credit decisions. Since, credit information is not mandatory for loan less than NRs.500,000 (approx. £ 5000) (Credit Information Centre, 2008) it could be argued that in other consumer lending except home loans (where the amount is more than NRs.500,000- approx £ 5000), the banks need to adhere to other risk management policies for example, credit scoring or seeking credit information from private credit rating companies.

4.2.2 Preliminary Establishment of Characteristics:

In the previous section, the findings of the questions related to an initial overview on the consumer credit from the perspective of the non-managerial staff were presented. Further, with an objective to identify the applicant's characteristics to assess their creditworthiness, the non-managerial staff was asked, *"while assessing the applicant's application for home loan, what weightage do you give to the following characteristics or variables?"*. From the application forms thirteen characteristics relating to applicant age, number of dependents, marital status, employment status, years of employment, monthly expenditure, loan-to-value ratio, collateral/ guarantee, property value, loans defaulted, total assets, property location and monthly income were identified.

As discussed within the literature, these characteristics have two common features: first is their potential soundness in helping to estimate the probability of default of an applicant; second are the potential of their combined explanatory power when a credit scoring method is employed to analyse an individual loan application when compared with historical data. These characteristics were scaled into a five-point likert scale using a standard set of responses which were- very important, important, moderately important, of little importance and unimportant. The respondents were asked to rank the level of importance they give to the characteristics from the applicant's application form while preparing the credit proposal or credit report for credit decision making by the credit officer/manager.

The thirteen characteristics were first subjected to a univariate analysis so as to analyse their distributional profiles and averages as presented in Table 4.1.

Table 4.1 Descriptive Statistics of the Preliminary Study Characteristics:

Characteristics		Mean[1]	Standard Deviation[2]	N[3]	Skewness[4]
1	Applicant Age	2.01	0.778	72	0.160
2	Marital Status	2.19	0.833	72	0.068
3	No. of Dependents	2.26	0.750	72	-0.278
4	Employment Status	1.64	0.635	72	0.475
5	Years of Employment	1.85	0.573	72	-0.004
6	Total Assets	1.13	0.335	72	2.292
7	Monthly Income	1.07	0.256	72	3.460
8	Monthly Expenditure	1.81	0.493	72	-0.409
9	Property Value	1.15	0.362	72	1.972
10	Property Location	2.03	0.691	72	-0.036
11	Loan to Value Ratio	1.26	0.444	72	1.094
12	Loans Defaulted	1.24	0.428	72	1.269
13	Collateral/Guarantee	1.31	0.493	72	1.220

1-Mean- signifies the average responses on the scale from being very important (1) to unimportant (5).
2-Standard Deviation (SD) - signifies how well the mean represents the data. Small SD (relative to the value of the mean) indicate the data points close to the mean and vice versa. A SD of 0 would mean that all the scores were the same.
3- N – number of samples
4-Skewness- Positive value of skewness represents a concentration of scores on the left of the distribution implying its importance, whereas negative values indicate a concentration on the right of the distribution implying unimportant.

(Source: Data Analysis Output from SPSS)

Majority of the respondents considered the characteristics such as applicant age, marital status, employment status, collateral/guarantee, loan to value ratio, loans defaulted, property value, total assets, monthly income as important (i.e. positively skewed), with only four characteristics such as number of dependents, years of employment, monthly expenditure and property location were considered as unimportant (i.e. negatively skewed). Thereafter, the overall reliability of the scale comprising the thirteen characteristics listed above was tested using Cronbach's Alpha Coefficient for the internal reliability. According to Pallant (2007), the

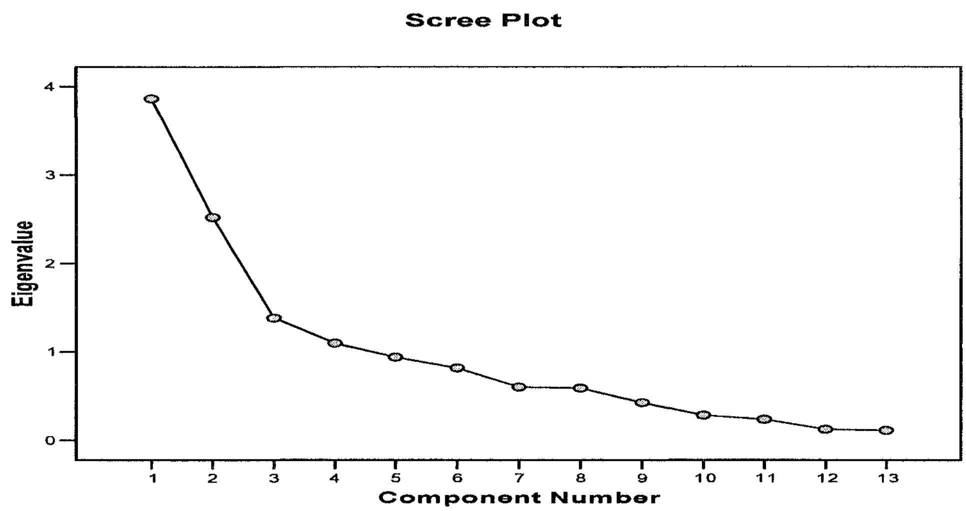
Cronbach's Alpha Coefficient of a scale should be above 0.7 for being reliable. It was found that the Cronbach's Alpha Coefficient 0.774, which suggested a high level of reliability. This suggested that the group of characteristics as perceived by the respondents have a reasonably high level of internal consistency.

Thereafter, exploratory factor analysis (as presented in Chapter Three) was used to reduce the number of characteristics from thirteen to a manageable number of potentially themed groups of characteristics. According to Hair *et al.,* (2003), in applying exploratory factor analysis the minimum sample size should be five times the number of characteristics or variables analysed. In this case, there were thirteen variables and with this assumption the sample should not be less then thirteen multiplied by five equals sixty five. Given the preliminary study consisted of seventy two respondents this suggest that application of exploratory factor analysis is potential viable.

As part of the exploratory factor analysis, the thirteen characteristics were first subjected to principal component analysis (PCA). Prior to performing PCA the suitability of the data for exploratory factor analysis was assessed. From the correlation matrix (attached in Appendix B4) we can infer that several significant correlations exist between the characteristics and if the correlation matrix equals to 0.002 (p-value) it could be suggested that data reduction via PCA could be performed (Field, 2005). Further, the trace of the correlation matrix equals to 13 which is just the number of characteristics (13) in the data set, confirming the applicability of the PCA analysis (Field, 2005).

To further support the viability of the exploratory factor analysis process, the Kaiser-Meyer-Oklin (KMO) and Bartlett's test were performed. The KMO result was 0.742 which exceeded the recommended value of 0.6 (Kaiser, 1974) and the Bartlett's result reached statistical significance (p=0.000) (attached in Appendix B5). These results supported the factorability of the correlation matrix. Thereafter, the results obtained after the PCA analysis was conducted (attached in Appendix B6), showed that out of the 13 components computed, the first four components recorded eigenvalues above 1 (3.862, 2.520, 1.383, and 1.098). These four components explain a total of around 68 per cent of the variance in the survey data. A further look at the scree plot presented in Figure 4.1, suggest that there is a clear break between the third and the fourth components. Hence, components 1, 2, and 3 explain more of the variance than the remaining components and should be retained.

Figure 4.1: Scree Plot of the Principal Component Analysis



*Eigenvalue: The eigenvalue of a factor represents the amount of the total variance explained by the factor (Pallant, 2007).
*Scree Plot: it is a graph plotting each component (X-axis) against its associated eigenvalue (Y-axis). It shows the relative importance of each factor. The graph has a very characteristic shape (there is a sharp decent in the curve followed by a tailing off) and the point of inflexion of this curve is used as the means of extraction (Field, 2000).

(Source: Data Analysis Output from SPSS)

Moreover, a parallel analysis was performed using the Monte Carlo PCA (attached in Appendix B7) and the results are summarised in Table 4.1. By comparing the eigenvalues obtained in the final part of the principal component analysis (attached in Appendix B6) with the corresponding first value from the random results generated by parallel analysis (shown in Table 4.2), it could be argued that only the first three components should be retained. The results of parallel analysis also support the decision from the scree plot (shown in Figure 4.1) to retain only three factors for further investigation.

Table 4.2 Monte Carlo PCA- Parallel Analysis Results.

Component No.	Actual Eigenvalue from PCA[1]	Criterion Value from Parallel Analysis[2]	Decision[3]
1	3.862	1.6432	Accept
2	2.520	1.4827	Accept
3	1.383	1.3526	Accept
4	1.098	1.2426	Reject
5	.942	1.1378	Reject

1-Actual Eigenvalue from PCA- this represents the value obtained from the principal component analysis performed through SPSS.
2-Criterion value from parallel analysis- the Monte Carlo principal component analysis obtained from Watkins (2000). Analysis attached in Appendix B7.
3- Decision Rule: if the actual eigenvalue is greater than the parallel analysis, accept the component and if less, then reject it. Thus, in the table 4.2 component 1, 2 and 3 are accepted.

(Source: Data Analysis Output from SPSS and Monte Carlo PCA)

In further support of the decision to retain the three factors rather than four factors, the component matrix (attached in Appendix B8) displays the loading of each of the items on the four components. From the component matrix, it could be see that most of the items load quite strongly (above 0.4) on the first three components. This support the conclusion derived from the scree plot (shown in Figure 4.1) and the parallel analysis (shown in Table 4.2) to retain only three factors for further investigation. The covariance score covariance matrix (attached in Appendix B9) for the principal components shows values of zero, since they are orthogonal to each other. To add to the interpretation of these three components, varimax rotation was performed and the rotated solution gives a total variance of about 59 per cent for the three components (attached in Appendix B10) which does not change after rotation. Finally, in the rotated component matrix, the loadings of each of the characteristics on the three factors are obtained (attached in Appendix B11). The main loadings on component 1 are applicant age, number of dependents, marital status and employment status. In component 2, collateral/guarantee, loan to value ratio, loans defaulted and property value are loaded. In component 3, property location and monthly income are loaded. Monthly expenditure, total assets and property location are loaded on more than two components. Thus, a clear pattern can be seen which allows each of the rotated factor to be given meaningful definition.

Factor 1 can be defined as the applicant's age, Factor 2 can be defined as applicant's collateral/guarantee and Factor 3 can be defined as applicant's monthly income. Thus, the exploratory factor analysis of the thirteen variables has developed a three-factor solution. The three factors account for an acceptable amount of around 60 per cent variance (attached in Appendix B10) and display logic in the combinations of the original characteristics. Thus, with this three factor solution instead of having to consider all the thirteen characteristics for the credit scoring model only about three characteristics- age, collateral and income could be considered.

Before proceeding to the next step of the research process which is expert interviews analysis, it is imperative to summarise the key points from the preceding preliminary study. The preliminary study was conducted to get an overview on the consumer credit risk and to establish the characteristics considered to be important in assessing the applicant for credit from the non-managerial perspective. With regard to the consumer credit policy, the non-managerial staff expressed that majority of the Nepalese banks have a risk management procedure in place in the form of a draft consumer credit policy, which is indifferent to the existing corporate credit policy. Since the two types of lending are different, it could be argued that a distinct credit policy for each type of lending would help to market the lending properly as per the risk appetite of the bank. Another key point was through the development of a formal risk rating technology, the credit could be priced according to the risk profile of the applicant. It was also suggested that through collateral/guarantee, establishment of risk department and obtaining credit information from credit bureaus would enhance risk management practices. Further, the exploratory factor analyses provided a three factor solution in terms of the applicant age, the collateral/guarantee and the monthly income as the characteristics which could be considered as important in assessing the creditworthiness of the applicant. The next step relates to the expert interview, which was conducted to get the views and opinions on consumer credit decision making from the managerial perspective. In the next section, the results and findings of the expert interviews are presented.

4.3 Expert Interviews:

As discussed in Chapter Three, expert interviews were conducted to explore softer issues relating to current consumer decision making, data handling and capture, model development, model implementation, model evaluation and model performance from the managerial perspective. The data were analysed using matrix analysis which has been discussed in Chapter Three. Through matrix analysis the expert interview transcripts were tabulated (attached in Appendix C5) so as to interpret and compare the contents of the expert knowledge. The major findings of the expert interviews process each carried out at one of the five different Nepalese banks identified as respondents A, B, C, D and E are discussed in the next section of the findings chapter:

4.3.1 The Credit Decision Process:

It was essential from the research perspective to gain an insight into the current credit decision making process within the Nepalese banking sector. The first question related to the credit decision process was *"how would you describe the current consumer credit decision process within your bank?"* From the responses of the interviewees, one of the major themes which related to the credit decision process was that it was based on the judgmental system. This is consistent with the literature which highlighted that the consumer credit decision is currently based upon the subjective or judgmental criteria (Ramamurthy, 2005; Nepal Rastra Bank, 2008). Moreover, respondent C commented *"all our credit application goes through the classic credit analysis process. This is an expert system wherein the five Cs of credit-character, capital, capacity, conditions and collateral of the applicant are analysed. This application are analysed against the five variables with reference to the set internal bank credit policy"*. According to Apilado *et al.*, (1974) the credit officers would consider the facets of character, capacity and collateral in evaluating the loan applications. The respective variables generally associated with the character of the applicant are age, sex, marital status, length of employment, purpose of the loan and the possession of a bank account. Those variables associated with the capacity of the applicant are amount of the loan, security (collateral/guarantee), terms of the loan, monthly income, the number of dependents and monthly expenditure. Further, respondents A and E reported that the credit proposals prepared as a result of the "*credit analysis process*" are screened by the credit control or risk assessment officer for risk and return trade off. This screening is done by the legal department in the case of bank C and D. However, in bank B the role of the legal department is to secure the collateral in the name of the bank. After all the initial evaluations, the credit proposals are forwarded to the lending authorities according to the policy of the bank for necessary approvals. In bank E, the role of the legal department is only for the legal documentation after the credit proposal have been approved. Hence, it could be inferred that there is no uniform standards and consistency in the credit decision making process across the participating banks. It could be argued that if Nepalese banks adopt an objective credit assessment framework on the lines of credit scoring as discussed within the literature, then the credit decision making process would be more consistent across the Nepalese banking sector.

With regard to the next question- "*to what extent do you and your colleagues in the credit department understand the various credit modelling techniques*" there was no consistent answer across the interviewees. Respondent A reported that they are working towards Asset Liability Management (ALM) and KYC (Know Your Customer). According to Bessis (2002), ALM relates to interest rate risk management and KYC to customer due diligence. Respondent B was not aware of the credit modelling techniques, but had undertaken a training course on credit risk management. Respondent C said that "*it has its own credit models for credit cards application which was transferred from the parent holding bank*", but the respondent did not specify whether the model was developed using the statistical techniques. Respondent E reported that they have developed an "*in-house risk assessment matrix* *model"*, but did not specify whether the model was based on statistical techniques. Further, it could be argued that the risk assessment matrix model might be similar to the judgmental scorecard (Caire, 2004) discussed within the literature. Thus, from the above responses, it could be inferred that majority of the interviewees did not understand clearly the complexities of the credit modelling techniques.

Thereafter, with regard to the next question- *"Is your credit decision based on judgmental or quantitative evaluation methods"*, all interviewees except respondent D confirmed that the credit decision was based upon the judgmental methods. However, respondent D emphasised that their credit decision were based upon *"value driven that represents a key element of a uniform, constructive and risk aware credit culture throughout the organisation"*. Within the literature, it has been established that consistency is desirable for two main reasons: *"at the risk management level, consistency is desirable if risk exposure levels are to be maintained and at the customer service level, consistency ensures that applicants are treated in an even-handed manner regardless of the channel by which they apply for loans"* (MacNeill, 2000) From the above responses, it could be suggested that in order to bring about a consistency in the credit decision, the credit decision process within the Nepalese banking sector should be uniform and based upon the risk management standards. With regard to the next question- *"what role do you think credit scoring would play in your credit granting decision processes"*, all the respondents emphasised that with the growth of consumer credit, Nepalese banks might develop or outsource credit scoring model in the future. Furthermore, the interviewees also agreed that credit scoring would play a fundamental role in the initial credit screening process, risk pricing, and risk management for the future consumer credit decision process within the Nepalese banking sector. However, respondent C raised the concerns about quality and quantity of data which would be needed for the development of the credit scoring model. Thus, the credit officers have confirmed that with the growth of the consumer credit portfolio within Nepalese banks it would be imperative to consider the adoption of an objective credit decision making process, which credit scoring potentially offer in the future.

4.3.2 Data Handling and Analysis

The most important factor which determines a uniform credit assessment framework is the availability of accurate information and the completeness of the customer data from sources both internal and external to the bank. To the question- *"to what extent can you rely upon the accuracy and completeness of customer data from sources both internal and external to your bank?"*. Respondent A commented that *"in terms of salaried individuals, the bank statements, cash flows, salary/rental and also the repayment sources (mixed)"*. Respondent B said *"it depends on the perception of the credit officer"*. These suggest that there is no defined bank policy in terms of customer data management, which raises a question in terms of consistent credit evaluation. Respondent C said *"Trust"* is the only way for verification of the customer information, but did not highlight how the bank would evaluate whether the information submitted are accurate and complete. Respondents D and E indicated that their respective banks verified the customer data with the help of assigned internal auditors and valuators. Thus, the accuracy and completeness of customer data internal to the bank depends upon the perception of the credit officers, internal auditors and credit control judgments. For customer data from external sources, respondent C raised a concern that where information from external sources was received in the form of salary slips; there was always a tendency on the part of the customer to inflate the salary with 60 per cent of the cases being accurate. This may imply that banks have to adopt additional measures to confirm the information and documents submitted by the applicant from external sources. Respondent D said that since there is "*no private credit bureau*", the bank would ask for certified statements to be presented by the customer, but did not specify who would certify those statements. Finally, respondent E stressed on the need for cross verification followed by documents backup so as to maintain the accuracy and completeness of customer data from sources external to the bank.

With regard to the next question regarding the verification of customer application forms and missing information, all the interviewees agreed that no credit decision would be taken until and unless all the customer information and missing data in the credit application forms and the supporting documents are completed. This meant that a high degree of due diligence is being observed with regard to the accuracy and completeness of the credit application forms. Supporting this argument respondent D said *"underwriting is typically conservative, not exactly risk averse but risk aware"*. Thus, it could be argued that while extending credit, the assessment process should consider the inherent risk and emphasise on measuring and management of the risk rather than avoiding the risk. Henceforth, the end use of the credit and the quality of credit are also significantly affecting the credit decision process. It was also apparent when respondent E said *"if there is no information in the application form, then the relationship officer would pursue with the applicant to get those information"*, which suggest that relationship officer would be engaged in chasing up the customers to complete the missing information rather than marketing of the credit products and services. This supports the earlier findings from the preliminary study questionnaires that relationship banking is still prevalent in the case of consumer lending especially home loans.

Further, to the question regarding *"the accuracy and honesty of the information provided by customers on their credit application forms"*, the interviewees said that they would cross verify the information presented on the application forms with the supporting documents submitted by the applicant. Further, the interviewees stressed that the banks would obtain credit reports on customers from the credit information centre and interbank references. According to the Nepal Rastra Bank's directives, it is a regulatory requirement to obtain credit reports for all lending in excess of NRs. 500,000 (approx. £5000) from the credit information centre (Credit Information Centre, 2008).

Further, the findings from the preliminary study questionnaires also confirms that all the Nepalese banks have been obtaining credit reports from the credit information centre, however the interviewees questioned on the credit reports being biased (as it gives information only on blacklisted borrowers) and not being up to date. With regard to obtaining interbank references, Ramamurthy (2004) suggested that due to the existence of multiple banking and a high level of competition, there is no smooth customer information sharing within the Nepalese banks. Thus, it could be inferred that that proper verification of the customer information from all sources (internal and external to the bank, credit information centre, interbank references) are important aspects of the credit assessment process in the Nepalese banking sector.

4.3.3 Model Development Issues:

From section 4.2.1 on the credit decision process, it could be inferred that credit scoring models have not been used in the Nepalese banks sector up to the time of this research and this research aims to determine to what extent are the development and implementation of an objective credit scoring models achievable within the Nepalese banking sector. Towards achieving these aims, it was important to know the views from the credit officers' perspective on –"*the use of historical data, whether the data would involve accepted customers, rejected customers, and/or accepted customers only with known outcomes*". From the interviewees' responses, the major theme to emerge was that the banks would use historical data for model development, which confirms the existing literature on the data handling (Lewis, 1992; Hand and Henley, 1997; Thomas, 2000; Liu, 2001; Bhatia, 2006; Crook *et al.*, 2007).

However, the interviewees were concerned about the challenges in maintaining the historical database of accepted as well as rejected customers. Respondent C emphasised that "*the database with a performance history of five years would be sufficient to develop a robust credit scoring model*". In the literature, it has been stressed that for a robust credit scoring model the data has to be from a single time period and from a population applying for a specific credit product (MacNeill, 2000). In regard to the next question on "*reject inference*", respondent A commented that they have been maintaining a backup file of rejected customers with reasons for rejection so that follow up may be made on the rejected applicants in the future subject to the change in the circumstances of the applicant. The importance of reject inference have been discussed within the literature and from the responses of the interviewees it could be confirmed that through the process of reject inference, banks would be able to study and review the possible outcomes of the loan had the loan been accepted. Thus, reject inference would provide the banks with the appropriate case for credit decision making and also if information on rejected applications are properly maintained, it could be built upon for future credit scoring modelling process.

One of the important elements for the modelling process is the range of characteristics to be considered in the model. The next question posed was- *"what range of variables/factors do you anticipate any formal model will consider, and in turn, include?"*, the interviewees said they would consider "*salary, age, profession, years of employment, demographic, geographic, purpose of the loan, collateral*" as the characteristics to assess the creditworthiness of the applicant. Nevertheless, respondent D emphasised on the "*applicant's willingness and ability to pay*". Within the literature, the willingness to pay is reflected by the character of the customer and the ability to pay is reflected by the customer's income and employment. Further, the age of the applicant is one of the important factors which determine the customer character. Boyle *et al.*, (1992) and Thomas (2000) have empirically confirmed that older borrowers are more risk averse and will therefore be less likely to default. However, for home loans within the Nepalese banking sector, an important criterion is that the gross monthly income of the borrower should be at least two times the equated monthly instalment of the loan. Further, the property in a home loan acts as a collateral in favour of the lender and since customers' own equity of about 20-30 per cent is invested in the house in the form of margin money, the propensity of default is minimised.

Thus, according to the interviewees the most important variables or factors which would be consider as the potential predictors of loan success or default are salary, employment, age and collateral. These findings also confirm the findings obtained during the preliminary study in which the factors found significant in assessing the creditworthiness of the applicant were applicant age, collateral/guarantee and monthly income.

With regard to the question- "*Are there any potential problems relating to scoring errors*", respondent B commented that *"the experience of credit officer might be lost if we use credit scoring"*. This response may imply that with the introduction of credit scoring models, the credit officers who consider themselves to be the "*lending mandates*" (Gardner *et al.,* 1999) might face the prospect of losing their position and expertise in the field of credit decision making. However, it could be argued that the credit officers' expertise could be used to complement the credit scoring model for credit decisions on extreme cases. Respondent C said that *"...in judgmental other factors play ...cannot capture all in scores"* which might suggest that since credit scoring models are based upon a fixed number of characteristics, any change in the present macroeconomic situation or the personal circumstances of the borrowers might not be reflected in the credit scoring models. On the other hand, the judgmental system would take into consideration the local knowledge, change in the borrowers' circumstances or any other changes which might result in scoring errors. Supporting the statement made above, respondent D said that *"There might be other factors like economic conditions, inflation which credit scoring might not consider wherein the judgmental system can come into play"*. Respondent E also emphasised that *"scoring is fixed, limited variables, so case to case basis should be adopted"*.

Thus, it could be argued that since the motivation behind the credit scoring system is to replace the current judgmental system with a more uniform and consistent system, the credit officers were seeing this as a danger in respect of their position to give expert credit decisions.

Another modelling issue which has been discussed within the literature relates to overrides in the credit decision process. Respondent A said *"local considerations"* which might be related to branch level issues, local knowledge of the area, and change in the circumstances of the applicants accounts for any overrides decisions. All the interviewees agreed that there are overrides taking place in the lending decisions and it is essential for the credit officers to consider overrides from the business point of view. However, such overrides should be measured and maintained and referred to for future credit decision making and also for the model development purposes.

4.3.4 Model Implementation Issues

With regard to the operational implementation of the credit decision models in the front line of the banking business, there were mixed responses such as – "*the sales department, head office, driven by business and credit, credit risk assessment department and credit control department*". This shows that the credit officers were not sure when to apply the credit decision models. MacNeill (2000) assert that *"the ideal location for credit scoring is at the customer interface*". Moreover, from the literature, it is known that application scoring models were applied for making credit decisions on new applicants and behavioural models were applied to supervise the existing customer for further credit (Thomas, 2000; Mays, 2004; Bhatia, 2006; Anderson, 2007). Further, with regard to the technical issues associated with the implementation of a quantitative credit decision model, respondent A said, *"software"*, respondents B and C said, *"infrastructure development and maintenance of historical data"*. However, bank D emphasised that *"the senior management of the bank is very positive about credit risk modelling and their emphasis on banks' soundness and stability"*. Thus, it could be inferred that development of proper infrastructures, software's, and maintenance of historical data backed by a strong management commitment to risk management were the technical issues associated with the implementation of the quantitative credit decision models in the Nepalese banking sector. Furthermore, with regard to the business issues associated with the implementation of the quantitative credit decision model, respondent D said, *"credit risk modelling is about managing it and not eliminating it. If we are able to properly manage it and bring about the Non Performing Loans (NPL) down then it would send a positive signal in the market."* In Chapter One, it was noted that the level of Non Performing Loans had declined from 22.8 per cent in Mid-July 2004 to 6.08 per cent in Mid-July 2008 (presented in Table 1.3), however the average capital adequacy ratio as in Mid-July 2008 stood at 4.04 percent below that Nepal Rastra Bank capital adequacy requirement of 11 per cent as against the Basel II guidelines for 8 per cent. This was mainly due to the large accumulated losses of two state-owned and one private sector bank (presented in Table 1.4). Thus, if it could be emphasised that through the adoption of quantitative credit decision models, the soundness and safety of the banks could be achieved then this will send a positive impact in the banking sector.

According to the interviewees, the cultural issues associated with the implementation of a quantitative credit decision models relate to the lack of an *"Act"* on consumer credit. Within the literature, reference was made to the existence of the Consumer Credit Act (1974) in the United Kingdom and the Equal Credit Opportunity Act (1974), was identified which guides the lender against discrimination in order to make unbiased credit decisions irrespective of race, colour, religion, sex, marital status, age or ethnic origin (Andreeva *et al.*, 2004). However, according to the Nepal Investment Climate Statement (2008), *"Foreign investors/nationals are permitted to acquire real estate in the name of the business entity they own, but are not allowed to acquire real estate as personal property"*. This statement suggests that only Nepalese nationals would be given credit, which is also evident from the requirements in the credit application form for a citizenship card or a passport to show that the applicant is of Nepalese origin. This is one of the major cultural issues which could create a problem in credit scoring models, which stresses the need to be unbiased.

Further, with regard to the model overrides, the interviewees were asked *"to what extent, if any, can those implementing the model override the model's decisions/ who triggers this override process?*. Respondent D commented that *"relationship manager and risk manager are separate, so there are no overrides. However, there might be overrides from the staff references which are negligible"*. From the literature, it is noted that banks may override credit decisions due to informational, policy and intuitional reasons (Lewis, 1992; Siddiqi, 2005; Anderson, 2007). However, a large proportion of overrides within the Nepalese banking sector may be attributed to *"staff references"* according to respondent B and *"pressure from the customer"* according to respondent E. However, due to the intense competition in the consumer banking, *"internal policy overrides"* may not be ruled out as mentioned by respondent A. Furthermore, respondent B stressed that *"sometimes to fulfil the credit targets, we as a credit department has to overlook overrides"*. This response by respondent B suggests that it is the banking pressure in terms of achievement of targets on the branch level which triggers overrides on credit decisions.

<u>4.3.5 Model Evaluation and Performance Issues</u>

The model evaluation and performance is related to the predictive power and the predictive accuracy of the credit scoring model. Given the option of adoption of the credit scoring model, the interviewees said that *"they would use a combination of the judgmental and the quantitative approaches to credit scoring because of the market requirement"*. It could be argued that since credit scoring models has not been used and the outcomes not know, the credit officers does not rule out the elimination of the judgmental system and replacing it by credit scoring models. Further, respondent B suggested that the credit evaluation through the experience of the credit officer will always play a vital role even if credit scoring models were adopted. This supports the views expressed by other interviewees that even if the banks choose to rely exclusively on the credit scoring models, they would undertake the assessment of any qualitative risk for cross validating the credit decisions. With regard to the validation of the credit scoring models, the literature suggests that the best practice is that once the model has been developed it has to be validated immediately so as to ensure that the model performance is compatible with the business as well as the regulatory compliance needs. However, the interviewees were of the opinion that the models have to be validated over a between two to three years. Perhaps, validation according to the credit officers might mean the review of the model, so as to ensure that the model is updated in accordance with the existing regulations as well as the change in the applicants' characteristics.

In terms of the performance criteria, the interviewees said that the performance would be determined by the *"repayments targets given by the head office, delinquencies and defaults (with a likely indicator of 30, 60, 90 days), relevance with the regulatory and Basel II requirements"*. However, from the responses it might be inferred that by performance criteria, the credit officers were referring to the existing credit decision making process. If the repayments were smooth and delinquencies and defaults were not observed then it would mean that the performance of the account is satisfactory. Further, from the literature it was indicated that Nepal Rastra Bank had formulated a loan classification and provisioning on funded outstanding (presented in Table 2.9), which directs Nepalese banks to make proper provisioning with regard to the performance of the loan. Furthermore, we can recall from chapter three the credit officers who participated in the first Quantitative Impact Study (QIS) of the Basel Accord Implementation Group set up by Nepal Rastra Bank were the interviewees in these expert interviews. Since they pointed out the regulatory and Basel II requirements as the performance criteria, it could be argued that Nepalese banks were moving ahead with the process for the implementation of the Basel II standards on the soundness and safety of the banking sector. Further, the interviewees made it clear that through proper customer education, the performance criteria related to the credit would be communicated.

Thereafter, the interviewees were asked whether behavioural scoring would help to reset the credit performance criteria in mortgage lending. To this, respondent D said *"mortgage lending which we call home loan is driven by the equated monthly* *instalments payment. If there is delinquency in the payment behaviour, the missed payments could be incorporated in the model, but that is a long way to go. First let us have the basic credit scoring model."* This suggests that the regular payment of the equated monthly instalments determines the credit performance criteria for home loans in the Nepalese banking sector. As long as there are no delinquencies in the payment history, the loan is satisfactory and the borrower might also be eligible for additional credits. Subsequently, with regard to the question *–"How long do you expect a scoring system to remain operational within your bank before updates take place and what performance criteria do you or expect to use to indicate it's time for replacement?",* the interviewees did not give any answer except respondent D who said, *"No idea as of now. Once we adopt any model we would see then".* Again, with regard to the next question- *"what would you anticipate the size and complexity of any credit scoring model to be in terms of the number of factors measured and scored",* there was no answer. This suggests that it was perhaps too early to ask the interviewees about the model replacement and also the size and complexity of the model, given that the model is yet to be developed and be used in the Nepalese banking sector. Thus, it could be taken as a positive argument to go forward to develop a bespoke credit scoring model for the Nepalese banking sector.

The final question related to monitoring the current level of customer evaluation system in terms of good decisions made for accepted loans. Respondent A said that they have "*a system in place*", but did not specify what type of system was in place. Respondent B emphasised that the "*repayment behaviour*" determines the good decisions made for accepted loans. Respondent C said "*they would abide by the group adoption of the Basel II regulations*", whilst respondent D suggests *"management information system. Portfolio basis by seeing the delinquency level"* and respondent E stressed, *"No hi-fi stuff. Informed education through judgmental"*. From this, it could perhaps be concluded that the credit officers viewed that if the repayments were satisfactory, it would imply a good decision made for accepted loans. Also, within the literature MacNeill (2000) has stressed if good data in terms of accepted as well as rejected applicants are incorporated in the model it would result in improved management information system for all future credit decision making process.

It is important to summarise the key point from the previous preliminary study and expert interviews analysis before proceeding to the next step of credit application forms data analysis for model development. From the non-managerial level preliminary study, it has been found that applicant age, collateral/guarantee and monthly income are the important characteristic which could be used to assess the creditworthiness of the applicant. Correspondingly, from the expert interviews, credit officers suggested that the potential predictors of a loan success or default are salary, employment status, applicant age and collateral/guarantee. Further, in terms of credit decision making process, the credit officers suggested that judgmental system was prevalent, however did not ruled out the possibility of adopting an objective credit decision making framework in the future. It was highlighted that without proper verification of the customer documents and filling the missing information on the application forms no credit decision would be taken.

The credit officers suggested that with regard to the accuracy and completeness of the information, cross verification through credit information centre and interbank references would be sought. In terms of model development, the credit officers expressed that good customer historical database with known outcomes as well as rejected applications would be essential. In terms of the model implementation, the credit officers expressed that the business needs and the management commitment were essential. Given the option for the adoption of the credit scoring models, the credit officers further suggested that they would use credit scoring models in complementary to the judgmental system. Thus, the preliminary study and expert interviews helped in the research process by exploring credit decision making process and modelling issues. In the next step, the findings from the credit application form data analysis and model development are presented.

4.4 Credit Application Forms and Model Development:

The preliminary study questionnaire and the expert interviews were helpful in the identification of the potential characteristics which the lenders would take into consideration to assess the creditworthiness of an individual loan applicant. From the preliminary study and the expert interviews it was found that the characteristics which could be considered as a measure of creditworthiness were applicant age, collateral/guarantee and monthly income, employment status.

As discussed in Chapter Three, it was emphasised that the credit application form data has to be from a single time period and from a population applying for a single credit product (MacNeill, 2000). Further, in terms of the sample size, Thomas *et al.*, (2002) recommended to use the full population rather than sampling from it. Thus, the customer application forms data to be considered in this study were recorded from the credit files of a population of 202 historical home loan customers of a typical Nepalese bank. The data were for home loans granted during the period of

2005-2006 (one year) and it was collected after a time horizon of one year (July 2007), so that both the borrower's characteristics as well as the default status could be observed (Bhatia, 2006). Though the characteristics were established through the preliminary study and later confirmed as a result of the expert interviews, it was imperative to test whether those characteristics were statistically significant when considered in the model development process. Thus, at the time of the data collection process from the credit files, twenty (20) characteristics and one status of the loan quality (default/bad credit and no default/good credit) were found. In the next step, the descriptions of these characteristics as well their preparation in terms of the coding regime to be considered for analysis are presented.

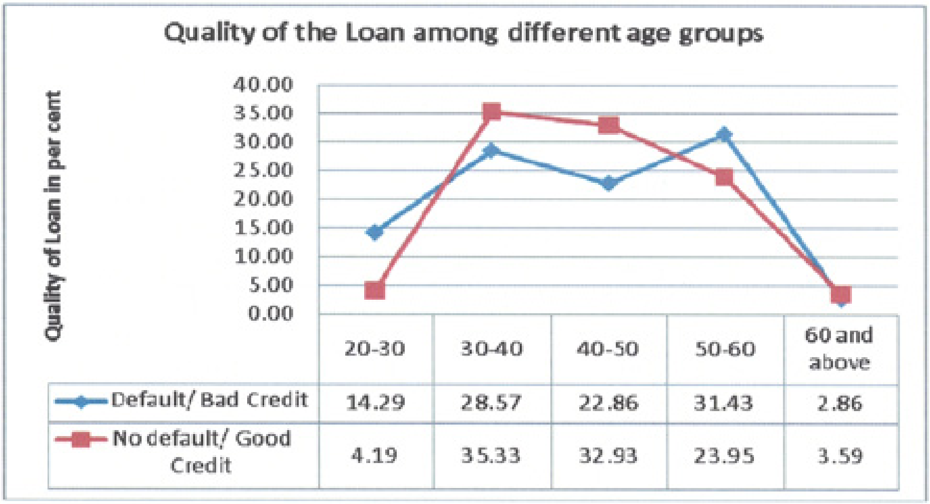
4.4.1 Description of the Characteristics and Coding:

The twenty (20) characteristics to be included for the purpose of model development are discussed in terms of their descriptions and coding regime for the purpose of analysis is presented as:

1. ***Applicant Age*** (X1) is the borrower's age in years. For our sample, the age characteristics has been categorised into five groups and coded as: 20-30 =1, 30-40 =2, 40-50 =3, 50-60 =4 and 60 and above =5. From the literature, we know that the eligibility condition for home loans in the Nepalese banks is that the applicant age has to be below 60 years of age. Further, Boyle et al., (1992) and Thomas (2000) have confirmed in their study that with the rise in the age of the applicant, the propensity to default is reduced. In our study, cross tabulation of the age of the applicant with the quality of loan was undertaken to assess any potential association. It can be seen from the Figure 4.2 that majority of the home

loans are in the age group 30-60 and the rate of default also increases with the increase in the age of the applicants, however in the age group 60 and above the defaults rate are low (2.86 per cent).

Figure 4.2: Quality of Loan among different age groups.

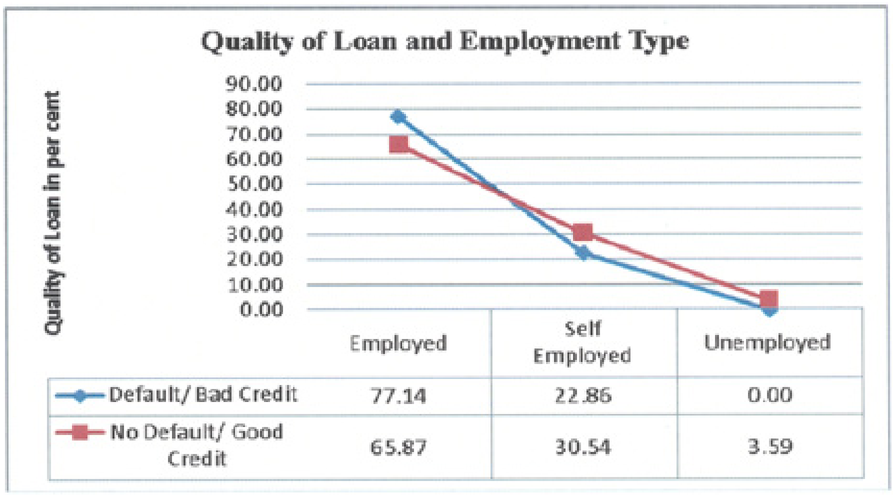


(Source: Data Analysis Output from SPSS)

2. ***Type of Employment*** (X2) describes the applicant being employed (coded as 1), self employed (coded as 2) and unemployed (coded as 3), which does not reflect the type of occupation the applicant holds. In the Nepalese banking sector, the type of employment determines the source of income for the applicant. From the literature, it has been established that the eligibility criteria for home loans in the Nepalese banks is that the applicant should be employed and this was also confirmed from the findings of the expert interviews. However, there might be cases where an applicant would describe as unemployed (housewife), but she might receive a regular source of rental incomes from the rental of her property. Further, when the type of employment was cross tabulated with the quality of the loan, the result in Figure 4.3 confirms that in the case of unemployed applicants

there were no defaults. However, in the case of employed applicants, 77.14 per cent were recorded as default/bad credit and 65.87 per cent as no default/ good credit. And, in the case of self-employed the rates of defaults/bad credit were 22.86 per cent and no defaults/good credits were 30.54 per cent. Thus, it could be inferred that the employment type is an important characteristic which determines the quality of the loan.

Figure 4.3 Quality of Loan and Employment Type:



(Source: Data Analysis Output from SPSS)

3. ***Type of Occupation*** (X3) is the job in which the applicant is engaged. In this study, the type of occupation is categorised into eleven categories and coded as farmer/agricultural (1), teacher/lecturer (2), housewife (3), government service(4), MNCs/NCs/banking(5), NGOs/INGOs(6), professionals(6), politician(7), entrepreneur/business(8), overseas employment(9), any other occupations(0). Out of the 202 sample analysed and presented in Table 4.3, it can be inferred that the highest number of defaults is in respect of applicants who were in the government service (9) and entrepreneur/business (9). Conversely, no defaults were recorded for

applicant who were categorised as farmer/agricultural, housewife and NGO/INGOs due to the low level of home loans granted (total 7 out of 202).

Table 4.3 Type of Occupation and the Quality of Loan Cross tabulation

Type of Occupation	Default/ Bad Credit	No Default/ Good Credit	Total
Farmer/Agricultural	0	2	2
Teacher/Lecturer	2	20	22
Housewife	0	6	6
Government Service	9	35	44
Multinational/National/Banking Corporations	7	31	38
NGO/INGOs	0	1	1
Professionals	4	20	24
Politician	1	1	2
Entrepreneur/Business	9	47	56
Overseas Employment	3	2	5
Any other occupations	0	2	2
Total	35	167	202

*the table represents the observed default/bad credit and no default/good credit in each type of occupation held by the credit customer. Out of the 202 sample, 35 default/bad credit was observed and 167 no default/good credit was observed.

(Source: Data Analysis Output from SPSS)

4.Office Telephone (X4) measures whether the applicant has an official telephone (coded as 1) or not (coded as 0). Crook *et al.,* (1992) reported that if the applicant does not have a telephone then the propensity of default is higher. However, from the results presented in Table 4.4, out of the 35 observed default cases, 32 borrowers had office telephone. Thus, we could argue that office telephone is a good determinant of default.

Table 4.4 Office Telephone and the Quality of Loan Cross Tabulation

Office Telephone	Default/ Bad Credit	No Default/ Good Credit	Total
No	3	33	36
Yes	32	134	166
Total	35	167	202

*Out of the 202 samples, 36 customers did not have office telephone and 166 had office telephone.

(Source: Data Analysis Output from SPSS)

5.Home Telephone (X5) measures whether the applicant has a home phone (coded as 1) or not (coded as 0). In Nepal, owning a home telephone is an indication of a good source of income and shows that the applicant can be contacted by the lender at any time. Also, possession of home telephone could suggest that the applicant is also regularly paying the telephone bills, which is further an indication of the behaviour of the applicant. However, from the results presented in Table 4.5, out of the 35 observed default cases, 32 borrowers had a home telephone.

Table 4.5 Home Telephone and the Quality of Loan Cross Tabulation

Home Telephone	Default/ Bad Credit	No Default/ Good Credit	Total
No	3	9	12
Yes	32	158	190
Total	35	167	202

*Out of the 202 samples, 12 customers did not have home telephone and 190 had office telephone.

(Source: Data Analysis Output from SPSS)

6.Number of Dependants (X6) corresponds to the number of individuals the applicant is supporting. No coding was done for this characteristic and the data was recorded as actual. This characteristic could be separated into two classes such as the number of children and the number of other dependants was done by Crook *et al.,* (1992). However, in Nepal the extended joint family system is still prevalent and so the total number of dependants would be considered for the purpose of this research. It could be argued that as the number of dependents increases, so does the applicant's expenditure and also the propensity of default (Thanh and Kleimeier, 2006).

7.Purpose of the Loan (X7) represents why the home loan has been requested for by the applicant. In the Nepalese banking sector, home loans are categorised for specific purposes as- for the construction of a house (coded as 1), for the purchase of a house/flat/apartment (coded as 2) and for the extension/repair/renovation of an existing house/flat/apartment (coded as 3). From Table 4.6, it can be inferred that the defaults are higher in cases of home loan taken for the construction of the house (68.57 per cent) and lower in the case of home loans taken for the purchase of house/flat/apartment (8.57 per cent). Thus, it perhaps could be argued that the purpose of the loan is a strong determinant of default in the case of home loans within the Nepalese banking sector.

Table 4.6 Purpose of the Loan and the Quality of the Loan Cross Tabulation

Purpose of the Loan	**Default/ Bad Credit**	**No Default/ Good Credit**	**Total**
Construction of the House	24	117	141
Purchase of the House/Flat/Apartment	3	33	36
Repair/Renovation of the House/Flat/Apartment	8	17	25
Total	35	167	202

*Home loans were given for the construction of the house, the purchase of the house/flat/apartment and repair/renovation of the house/flat/apartment. The table shows the default as well as no default status in each purpose of the home loan application.

(Source: Data Analysis Output from SPSS)

8.***Total Cost of the Project*** (X8) represents the total cost price of the house/flat/apartment or the construction cost of the house or the renovation/repair/renovation cost of an existing house/flat/apartment. The applicant has to submit a project report prepared by an approved consultant of the bank highlighting the cost of the project. For the purpose of model development, this characteristic is considered in actual figures.

9.***Loan Amount Requested*** (X9) is the amount of home loan requested by the applicant and is coded as actual for the purpose of analysis. From the literature, it is known that the applicant has to contribute a margin amount which is about 20-30 per cent of the total cost of the project from his own equity in the Nepalese banking sector. However, there might be circumstances that the total loan amount requested might not be granted by the bank, if the bank is not satisfied with the applicant's contribution. Since, this characteristic is directly related to the amount to be sanctioned by the bank, it could be argued that the loan amount requested might be a determinant of default.

10. ***Other Sources of Finance*** (X10) represents the fund available to the applicant from other sources such as loans/grants from relatives, interests on deposits, rental income, dividends, and sale of other property which the applicant could utilise to contribute towards the project cost. Other sources of finance also show that the financial prosperity in terms of the applicant, which is an indicator of good credit risk. For the purposes of this analysis, the data is taken on an actual basis.

11. ***Stage of the Project*** (X11) represents the phase of the project. The data collected were coded as Not Started (coded as 0), Foundation completed (coded as 1), Structural work completed (coded as 2), Repairs and Finishing (coded as 3) and Purchase of house/flat/apartment (coded as 4). From the literature, it has been established that for the purchase of a house/flat/apartment or renovation, the home loan is granted outright subject to the borrower's margin contribution. However, for the construction of a new house, the home loan is granted on an instalments basis in which the borrower has to first build the initial foundation of the house from his own equity, before the bank will release any of the loan requested. Thus, the bank ensures that the borrower is concerned about building the house from the loan which ensures that the risk of default is minimised. However, from the analysis presented in Table 4.7 it can be seen that there were thirty one (31) home loans granted for work not started and of these six (6) were in default. In this case, it could be concluded that the bank has not been adhering to the guidelines in its credit policy document.

Table 4.7 Stage of the Project and the Quality of the Loan Cross Tabulation

Stage of the Property/Construction	Default/ Bad Credit	No Default/ Good Credit	Total
Not Started	6	25	31
Foundation Completed	9	47	56
Structural Work Completed	10	43	53
Repairs and Finishing	7	19	26
Purchase of House/Flat/Apartment	3	33	36
Total	35	167	202

*Home loans were given considering the different stages of the property/construction such as not started, foundation completed, structural work completed, repairs and finishing and purchase of finished house/flat/apartment. The table shows the default as well as no default status in each stage of the project.

(Source: Data Analysis Output from SPSS)

12. ***Total Assets of the Applicant*** (X12) represents all the assets that the applicant has in the form of savings deposits with the bank or any other financial institutions, investments in shares and securities, furniture, fixtures and home appliances, ownership of motor vehicles, jewelleries and any other assets. In Nepal, it is interesting to note that the applicant would include all possible assets owned and also sometime exaggerate these it as the bank does not usually ask for the documentary proof of the assets. For the purpose of this analysis, the assets were recorded as actual.

13. ***Total Liabilities of the Applicant*** (X13) measures all the liabilities of the applicant which might be loans from the bank, loans from other financial institutions, loans from an employer and any other liabilities. It is interesting to note that during the process of data collection, this characteristic was found missing from the majority of the credit application forms. From the expert interviews, it was established that without the completion of all missing information in the credit application forms the banks would not grant any loan. However, in this case the home loans were granted without this characteristic

being adhere to. For the purpose of analysis, the liabilities were recorded as actual.

14. ***Monthly Income of the Applicant*** (X14) represents the applicant's ability to repay and it is consider on an actual basis for the purpose of analysis. Within the Nepalese banks, one of the conditions for home loans is that the monthly income of the borrower should be twice the repayment amount. In this regard, the bank would require the applicant to submit a salary slip or a salary certificate issued by the applicant's employer stating the current monthly salary, the applicant's position, the terms of employment and the remaining tenure of the employment. Further, this characteristic was found to be significant in the preliminary study questionnaires as well as by the expert interviews to be considered in the credit decision making process to assess the creditworthiness of the borrower.

15. ***Monthly Income of the Spouse*** (X15) represents the income of the applicant's spouse and is consider on an actual basis for the purpose of analysis. In the case of joint borrowings, the income of the spouse is also taken into consideration for the purpose of the assessment of the loan.

16. ***Total Monthly Income (Self and Spouse)*** (X16) measures the total income of the applicant and spouse and is consider on an actual basis for the purpose of analysis. The total income represents the applicants' financial wealth and his ability to pay.

17. ***Applicant's Equity*** (X17) represents the applicant's contribution towards the project cost (also known as loan to value ratio). Nepalese banks specify applicant equity between 20-30 per cent in the property before the loan is sanctioned. A

high percentage of borrowers' equity could signify low defaults rates. This characteristic was considered as actual for the analysis.

18.Rate of Interest (X18) represents the cost of the loan and considered as actual for the purpose of analysis. This is the interest charged to the applicant for the loan amount as per the published rate of the bank. This characteristic is taken as actual for the purpose of analysis.

19.Loan Duration (X19) represents the maturity (or term) of the loan in years. The loan duration is decided by the bank taking into account the borrower's repayment ability. In the Nepalese banking sector, the maximum tenure for the home loans is 25 years. However, from the analysis presented in Table 4.8 it could be suggested that no home loans have been granted for duration in excess of 20 years for this sample and the default rates is high for loan between 5-15 years.

Table 4.8 Loan Duration and the Quality of the Loan Cross Tabulation

Loan Duration	Default/Bad Credit	No Default/Good Credit	Total
0-5 years	7	18	25
5-10 years	14	68	82
10-15 years	11	73	84
15-20 years	3	8	11
20-25 years	0	0	0
Total	35	167	202

*This table shows the default or no default status in different categories of the loan duration.

(Source: Data Analysis Output from SPSS)

20.Property Value (X20) represents the value of the property (also known as collateral value) considered in actual for the purpose of analysis. The property serves as collateral in the case of home loan and is secured in favour of the lender. The higher the value of the property, the higher is the motivation for the borrower to repay the loan outstanding as the borrower might not want to loose the property. From the literature, it was established that the propensity to default is higher in the case of negative equity, which is when the value of the property is less than the amount of the home loan. For the purpose of analysis, this characteristic is taken in actual figures.

21. ***Quality of the Loan*** (Y) is the dependent characteristic to be considered in the model which is coded as 0 for default/bad credit and 1 for no default or good credit. This the credit behaviour of the customer to whom the home loan was granted. From 202 home loans 167 (82.67 per cent) were non default or good status and 35 (17.33 per cent) were in default or bad status.

4.4.2 Model Estimation and Development:

It has been illustrated above that both categorical and continuous characteristics would be consider in the model. As discussed in Chapter 3, for a new market which does not have history of credit scoring, (Crook *et al.,* 2007) recommended logistic regression as the most appropriate statistical technique for model development as it is statistically more acceptable and the resulting scores can provide estimates (Henley, 1995; Sidiqqi, 2005; Anderson, 2007). Logistic regression as the method of choice has been discussed within the literature in Chapter Two and model development method in Chapter Three.

Before proceeding to model development, it is essential to check for multicollinearity among the characteristics (Pallant, 2007). According to Crook *et al.,* (1992, p.225), *"if multicollinearity is high, then the matrix of standard coefficients is an unreliable guide to the relative contribution of each characteristics and the rankings on the* *matrix would differ considerably".* Menard (1995) suggested that a tolerance value less than 0.1 indicates a serious collinearity problem. From the correlation coefficients results (attached in Appendix D1), it could be inferred that monthly income (tolerance value = 0.003) is highly correlated with the predictor characteristics.

Further, Myers (1990) illustrated that if the Variance Inflation Factor (VIF) value is greater than 10, then it is a cause of concern. In our analysis presented in Appendix D1, the VIF in case of monthly income is 398.791, which also indicates the multicollinearity with the predictor characteristics. Further, examining the collinearity diagnostics results presented in Appendix D2, it could be inferred that the eigenvalues (14.131) clearly indicates that the solutions of the parameters might be affected by a small change in the predictors (Field, 2005).

According to Sharma (1996, p. 329), in "*the case of multicollinearity, the backward stepwise method is ideal because it includes the best set of independent characteristics to the model."* So, in order to estimate the model, the backward stepwise logistic regression analysis were used to select most significant characteristics out of the 20 characteristics discussed above to be included to the model. At the starting point, the model contains all the 20 characteristics. Thereafter, at each step, the backward stepwise method eliminates the weakest characteristics so that only the strongest predictors are considered for the final model.

After fourteen (14) steps, the backward stepwise process ends up with six (6) characteristics such as type of employment (X2), type of occupation (X3), purpose of the loan (X7), total cost of the project (X8), loan amount requested (X9) and stage of the project (X11) to be included to the final model. The remaining fourteen (14) characteristics were not included in the model because they had insignificant coefficients and did not contribute to the explanation of the dependent characteristic's variance and also they were highly correlated with the included characteristics. These characteristics as well as their coefficients are summarised in Table 4.9.

Table 4.9 Logistic Regression Final Model Parameters:

Characteristics	Coefficients (B) [1]	Standard Errors [2]	Wald [3]	P-Values [4]	Exp (B) [5]	Lower 95% C.I. for Exp (B) [6]	Upper 95% C.I. for Exp (B) [7]
Type of Employment (X2)	**1.5054261**	0.5980502	6.3364158	0.0118284	4.5060732	1.3955231	14.5498815
Type of Occupation (X3)	**-0.3110066**	0.1141474	7.4234661	0.0064379	0.7327091	0.5858266	0.9164189
Purpose of the Loan (X7)	**-0.8348210**	0.3237010	6.6511809	0.0099090	0.4339521	0.2300949	0.8184207
Total Cost of the Project (X8)	**-0.0000004**	0.0000002	4.7436454	0.0294067	0.9999996	0.9999993	1.0000000
Loan Amount Requested (X9)	**0.0000005**	0.0000003	3.9529864	0.0467883	1.0000005	1.0000000	1.0000011
Stage of the Project (X11)	**0.3737026**	0.1882177	3.9421338	0.0470910	1.4531049	1.0048143	2.1013971
Constant	**2.3645648**	0.7985188	8.7686390	0.0030645	10.6394076		

1-Coefficients (B) represent the estimates of the predictors (β) and the constant (α) included in the model. This value needs to be replaced in the equation to establish the probability that a case falls into certain category.
2-Standard Errors (SE) are the standard deviation of the sample distribution. A small SE signifies that most pairs of samples will have very similar means. A large SE would tell that the sample means can deviate quite a lot from the population mean and so differences between pairs of samples can be quite large by chance alone.
3- Wald statistic has the chi-square distribution and tells whether the coefficient (B) for the predictor is significantly different from zero. If the coefficient is significantly different from zero, than it could be inferred that the predictor is making a significant contribution to the prediction of the dependent variable (Y)
4- P-values represent statistical significance of the predictor.
5- Exp (B) represent the odds ratios (OR) for each of the predictor. According to Tabachnick and Fidell (2007, p. 461), the *"OR represents the change in odds of being in one of the categories of outcome when the value of the predictor increases by one unit".*
6 & 7- For each OR, Exp (B) the lower value and upper value at 95% confidence limit is presented. This shows the range of values at 95% confident encompassing the true value of the odds ratio.

(Source: Data Analysis Output from SPSS)

The six characteristics in combination with each other are statistically significant in predicting the quality of the home loan. The results of the logistic regression suggests that the type of employment (X2) characteristic is highly significant (β =1.5054261 and p-values =0.0118284) which means that type of employment is one of the most important predictor of the quality of home loans. Other significant predictors are the type of occupation (X3),the purpose of the loan (X7), the total cost of the project

(X8), the amount of loan requested (X9) and the stage of the project (X11). The p-values shows the levels of statistical significance associated with the characteristics in the model. For a given type of occupation, purpose of the loan, total cost of the project, the amount of loan requested and the stage of the project, the type of employment is a significant predictor at the 5% level (p-value = 0.0118284). For a given type of employment, purpose of the loan, the total cost of the project, the amount of loan requested and the stage of the project, the type of occupation is a significant predictor at the 1% level (p-value = 0.0064379). For a given type of employment, type of occupation, the total cost of the project, the amount of loan requested and the stage of construction, the purpose of the loan is a significant predictor at the 1% level (p-value = 0.0099090). For a given type of employment, type of occupation, purpose of the loan, the amount of loan requested and the stage of construction, the total cost of the project is a significant predictor at the 5% level (p- value = 0.0294067). For a given type of employment, type of occupation, purpose of the loan, the total cost of the project and the stage of construction, the loan amount request is a significant predictor at the 5% level (p- value = 0.0467883). Finally, for a given type of employment, type of occupation, purpose of the loan, the total cost of the project, and the amount of loan requested the stage of construction is a significant predictor at the 5% level (p- value = 0.0470910).

Thus, the logistic regression equation of our model is given by:

$$P(Y) = 1/\left(1+e^{-Z}\right) \qquad \textbf{(Equation 4.1)}$$

Where $Z = 2.3645648 + 1.5054261\ X2 - 0.3110066\ X3 - 0.8348210\ X7 - 0.0000004\ X8 + 0.0000005\ X9 + 0.3737026\ X11.$

Thus, the credit scoring model generated from the historical customer data could be applied to new customer to predict their unknown value of the dependent variable 'Y'. Thus a credit decision is made based on the prediction of 'Y'. The prediction can either be the risk class with two categorical values or a continuous score (from 0% to 100%, which may for example be the default probabilities). It has been discussed within the method of model development presented in Chapter Three that although the dependent characteristic takes values 0 and 1, the logistic regression equation does not give the prediction of 0 and 1. The logistic regression equation of linear combinations of independent characteristics gives the log odds, which would be transformed to the probabilities of default, which is then compared with the cut off value of 0.50 (the cut-off value is the value which maximises the model accuracy and in this model it is taken as 0.5). Thus, if the probability of default is less than 0.50 (50%), then the applicant would be accepted and classified as a good credit and if the probability of default is classified greater than 0.5 (50%), then the applicant would be rejected as classified as a bad credit.

4.4.3 Model Performance:

In order to test the performance of the model several goodness of fit test were conducted. The results of the omnibus tests of model coefficients presented in Appendix D3 gives us an indication of how well the model performs when the predictors were entered to the model. The significance value is 0.003 (as against the standard rule significance value should be less than 0.005) which confirms that the model performance has been good.

Another model performance test in the Homer and Lemeshow Test, in which poor model fit is indicated by a significance value less than 0.05. In the results presented in Appendix D4, the significance value is 0.276, which supports the performance of the model.

The model summary (attached in Appendix D5) gives information about the usefulness of the model. The Cox & Snell R Square (0.092) and Nagelkerke R Square (0.154) suggest that approximately between 9.2 per cent and 15.4 per cent variation of the dependent variable is explained by the above six predictors in the final model.

As discussed within the literature, the performance of the model could be ascertained by calculating the classification accuracy generated by the model which is presented in Table 4.10. The percentage of correctly classified bad credit (PCC bad) is 8.6 per cent (that is only 3 out of the 35 bad credits were correctly classified) and the model could classify 99.4 per cent of correctly classified good credit (PCC good) which indicates that out of the 167 good credits, 166 were classified correctly.

Table 4.10: Classification Matrix of the Final Model (at Cut off value = 50%)

Observed			Predicted		
			Quality of the Loan		
			Default/Bad Credit	No Default/Good Credit	Percentage Correct
Step14	Quality of the Loan	Default/Bad Credit	3	32	8.6
		No Default/Good Credit	1	166	99.4
		Overall Percentage			83.7

a. The cut value is .500

(Source: Data Analysis Output from SPSS)

The final model has a total classification accuracy of 83.7 per cent at a 50% cut-off level, which is good when compared with Srinivasan and Kim (1987) - 89.3 per cent; Henley (1995) - 43.3 per cent; Desai *et al.,* (1997)- 43.3 per cent; West (2000) -81.8 per cent; Lee et al., (2002)- 73.5 per cent and Baesens *et al.,* (2003)- 79.3 per cent. However, the final model obtained has a limitation, as it cannot predict the bad debt which might be overcome by adding other explanatory characteristics. As described by Baesens *et al.,* (2003), the model classification might result in two types of errors:

- Type I errors (bad credit classified as good- Bg)
- Type II errors (good credit classified as bad- Gb).

From the lender's perspective, type I errors are more alarming than type II errors because the bad applicant would be classified as good applicant. As discussed within the literature, the sensitivity (SENS) which is the proportion of correctly classified good credit to the total number of predicted good credit and specificity (SPEC) is the proportion of correctly classified bad credit to the total number of predicted bad credit could be calculated for the model classification matrix (cut off value =0.50) as:

$$\text{SENS} = \text{Gg} / (\text{Gg} + \text{Bg})$$

$$= 166/(166 + 32) = 0.8383 = 83.83\ \%$$

$$\text{SPEC} = \text{Bb} / (\text{Bb} + \text{Gb})$$

$$= 3/(3+1) = 0.75 = 75.00\ \%$$

Since, type I errors are more serious, the model could be calibrated (meaning to determine the optimal cut-off point) based on the sensitivity (SENS) measures.

In order to calibrate the model it is possible to assume that the Nepalese bank wanted to set a target for non-performing home loans at 0.75 per cent (as against the Mid-July 2008 NPL of 6.08 per cent of Class A Nepalese Commercial Banks presented in Table 1.4), then it could calibrate the model to a sensitivity of 99.25 per cent (SENS =100% - 0.75%), which could mean that the Nepalese bank should only accept applicants who have a predicted probability of default of less than 0.75 per cent. With such a cut-off value, the modified classification matrix would be as presented in Table 4.11.

Table 4.11: Modified Classification Matrix (at Cut off value = 75%):

Observed			Predicted: Quality of the Loan: Default/Bad Credit	Predicted: Quality of the Loan: No Default/Good Credit	Predicted: Percentage Correct
Step14	Quality of the Loan	Default/Bad Credit	14	21	40.0
		No Default/Good Credit	20	147	88.0
		Overall Percentage			79.7

a. The cut value is .750

(Source: Data Analysis Output from SPSS)

By comparing the accuracy of the modified classification matrix (cut off = 0.75) with the original classification matrix (cut off = 0.50), the PCC good drops from 99.4 per cent to 88 per cent and PCC bad increases from 8.6 per cent to 40 per cent.

SENS = 147 / (147 + 21) = 0.8721 =87.21%

SPEC = 14 / (14 +20) = 0.4117 =41.17%

Thus, an improvement of 3.38 per cent (87.21%-83.83%) in sensitivity is achieved at a cost of a 33.83 per cent (75.00%-41.17%) reduction in specificity. This means that by calibrating the cut-off value of the model, the percentage of bad credit being classified as good would be reduced.

4.5 Chapter Summary:

In summary, this Chapter has discussed the findings from the mixed methods research approach comprising of preliminary study, expert interviews and credit application forms leading to the model development. In the first step, the preliminary study was conducted through the questionnaire survey targeted to the non-managerial staff working in the Nepalese banking sector to get an initial overview on consumer credit risk and the preliminary establishment of characteristics considered as important in assessing an applicant for consumer credit. With regard to consumer credit risk, the non-managerial staff expressed that with a distinct consumer credit policy document, establishment of a risk management department, obtaining credit information on borrowers from the credit information bureaus would enhance risk management practices in Nepalese banks. Moreover, while assessing the creditworthiness of the applicant three characteristics relating to applicant age, collateral/guarantee and monthly income could be considered.

In the next step, the expert interviews were conducted with the managerial level to explore softer issues relating to current credit decision making, data handling, model development, model implementation, model evaluation and performance. The findings suggest that credit decisions were made based upon the judgmental system, however did not ruled out the possibility of adopting an objective approach in the future because of business needs. In terms of data handling, the credit officers insisted that without proper verification and completeness of the credit application forms and necessary supporting documents, no credit would be granted. The credit officers also suggested the potential predictors of a loan success or default were salary, employment status, applicant age and collateral/guarantee. With regard to model development, the credit officers expressed that quality customer historical database with known outcomes, reject inference is essential. In terms of the option of adoption of a scoring model, the credit officers suggested that they would use the credit scoring model as supplementary to the existing credit decision making framework.

In the final step, historical customer data relating to home loans were collected from the credit application forms (kept as credit files) of a typical Nepalese bank and analysed so as to develop the credit scoring model. Though potential characteristics were established during the preliminary study and later confirmed as a result of the expert interviews, it was imperative to test whether those characteristics were statistically significant when considered in the model development process. In the final model out of the twenty characteristics, six characteristics relating to the type of employment, type of occupation, the purpose of the loan, the total cost of the loan, loan amount requested and the stage of the project were considered to be the potential predictor of the quality of home loans. The final model had a classification accuracy of 83.7 per cent at a 50% cut-off level, which is good (compared with Srinivasan and Kim (1987) - 89.3 per cent; Henley (1995) - 43.3 per cent; Desai *et al.,* (1997)- 43.3 per cent; West (2000) -81.8 per cent; Lee et al., (2002)- 73.5 per cent and Baesens *et al.,* (2003)- 79.3 per cent). However, the final model obtained has a limitation, as it cannot predict the bad debt which might be overcome by adding other explanatory characteristics. Thus, this research has achieved its objective to develop a model for the Nepalese bank which previously did not have a history of credit scoring.

Chapter 5: Conclusions, Contributions and Research Implications:

5.1 Introduction:

At the outset of this research, the principal aim identified in Chapter One was to identify whether the development of an objective credit scoring model was achievable within the Nepalese banking sector. This aim led the researcher to conduct an extensive literature review on consumer credit and credit scoring (presented in Chapter Two), thereby identifying the gaps in the literature (presented in Chapter Three). Thereafter, the research questions were formulated and the pragmatist paradigm with a mixed method approach comprising of the both the qualitative (expert interviews) and quantitative methods (questionnaire and credit application forms) were adopted to conduct supporting primary research. Sequentially, the data were analysed and findings were presented and discussed in Chapter Four.

Towards the end of this research journey, this chapter presents the conclusions to the research process by discussing the findings with reference to the research questions. Thereafter, contributions of the research and implications to professional practice are presented. Subsequently, the reflections on the research are presented by identifying the limitations and how this could be improved to benefit future researchers intending to conduct a similar study in a different setting. And finally, the future directions and recommendations for research around the area of credit scoring and consumer credit risk management and personal reflections are presented. The chapter then concludes with a chapter summary.

5.2 Discussion of the Findings with reference to the Research Questions:

The outcome of a piece of business and management research is its ability to answer the research questions posed and also provide a direction for future research. The discussion of findings with the research questions provides the opportunity to ascertain whether the research was able to provide logical answers to the research problem presented. As the sub-questions of the research contribute substantially to answer the main research question, the sub-questions would be discussed first.

The first sub-question was: *What is the best method/way to evaluate the creditworthiness of the applicants?*

This question was answered through the extensive literature reviews and the preliminary study and expert interviews. From the literature, we know that "creditworthiness" is an attribute which makes the candidate suitable for the grant of credit, meaning that the candidate would pay all his obligations as per the terms and conditions of the credit. However, creditworthiness is something which is very abstract until measured. Traditionally, in order to measure creditworthiness, lenders used a subjective framework based on the industry wide acronyms such as the Cs (character, capital, collateral, capacity and conditions), PARTS (purpose, amount, repayment, term and security) and CAMPARI (character, ability, margin, purpose, amount, repayment and insurance) to guide their judgmental credit decisions (Thomas, 2000). However, this subjective framework was not free from some of its weaknesses such as the credit officer errors, inconsistency in its application between credit officers, high costs associated with training and employing credit officers, slow credit decisions, inability to consider the high volumes of credit applications and the lack of quantification of the inherent credit risk.

However, with the remarkable growth of the consumer credit market it became less convenient for the lenders to use the subjective framework to assist their judgmental credit decision making (Hand, 1998). Thus, the lenders advocated for an alternative approach which is objective, fast, reliable and consistent and could handle the high volume of credit applications. This led to the development of an objective framework based on statistical techniques (known as credit scoring) by Durand (1941) for the United States National Bureau of Economic Research to investigate instalments loans (Hand and Henley, 1997). Since, then the credit scoring systems has been used extensively to guide lenders in their credit decision making process. Credit scoring has come of age and is being widely used for marketing, application processing, account management, collection and recoveries and also fraud management (Anderson, 2007).

Consumer credit started to grow significantly within the Nepalese banking sector from the year 2002 and the growth has been accelerating over recent years. From the literature, it has been established that judgmental decisions based upon the subjective framework have been predominantly used across the Nepalese banking sector to assess and evaluate the creditworthiness of the applicant (Ramamurthy, 2004; Upadhyay, 2005; Nepal Rastra Bank, 2005). From the preliminary study, it could be inferred that the majority of Nepalese banks had a consumer credit policy to guide their credit decisions, but these policy frameworks were no different to the corporate credit ones. This suggests that the credit decision making framework has been the same as for corporate credit, which is based on the subjective framework using industry wide acronyms. Further, the findings from the expert interviews suggest that the credit officers have been using a judgmental framework based on the subjective assessment of the credit applications to inform their credit decisions. The credit officers also suggested that the judgmental credit evaluation method was part of the wider credit analysis process, in which the credit proposals were evaluated by several hierarchical authorities before arriving to a credit decision. However, it was suggested that with the growth in the consumer credit market in the Nepalese banking sector, an alternative to the present system of credit granting would be expected. The alternative system is expected to be objective, fast, reliable and consistent, and would have the capacity to handle a high volume of customers for credit. Thus, it is the demand from the market and the business needs of the Nepalese banks, would jointly decide the best method/way the applicants' are assessed for creditworthiness.

The second sub-question was: *What are the factors/characteristics that lenders should consider while assessing an application for consumer credit?*
Within the literature the factors/characteristics that the lenders would consider while assessing an application for consumer credit could be grouped as demographic, financial, employment, behavioural which has been discussed in Chapter Two. The lenders would consider these characteristics according to their predictive power, informational content, correlations, and legal compliance. This research took a mixed methods approach (triangulated) through the use of questionnaire, expert interviews and the credit application forms data to answer this question.

The preliminary study was conducted as part of the research process to establish the characteristics which the lenders would consider while assessing an application for consumer credit. Thirteen characteristics relating to applicant age, marital status, number of dependents, employment status, years of employment, monthly income, monthly expenditure, collateral/guarantee, loan-to-value ratio, loans defaulted, property value, property location and property value were selected from the application forms of Nepalese banks. Thereafter, these characteristics were scaled into a five-point likert scale using a standard set of responses which were - very important, important, moderately important, of little importance and unimportant. Thereafter, the respondents were asked to indicate the importance they attach to the characteristics while preparing the credit proposals. Further, the findings of the exploratory factor analysis of the questionnaires suggest a three factor solution in which applicant age, the collateral/guarantee and the monthly income were found significant in assessing an application for consumer credit.

Working on the results obtained from the preliminary study questionnaires, it was imperative to get the credit officer's expert opinion on the range of characteristics which they would consider as a potential predictor of the quality of loan. It has been suggested that the most potential predictors of a loan success or default were salary, employment, applicant age and collateral/guarantee.

Though the characteristics were established through the preliminary study and later confirmed as a result of the expert interviews, it was important to establish the characteristics objectively. In this process, the credit application forms data relating to twenty characteristics were gathered from a Nepalese bank. After necessary coding and data preparation process, the twenty characteristics (as presented in Chapter Four) were modelled using logistic regression to find out the best predictor of the quality of home loans. In the final model, six characteristics such as the type of employment, the type of occupation, the purpose of the loan, the total cost of the project, the amount of loan requested and the stage of the project were found to be significant predictors of the quality of credit (default or no default). Further, the predictive accuracy of the model was found to be 83.70 per cent (at cut off value 50%) suggesting that the six characteristics were important in objectively assessing the consumer for credit (this can be compared with the relative predictive accuracy presented in Table 2.7). Henceforth, it could be suggested that the method of assessment (subjective or statistical) determines the factor/characteristics to be considered to assess the creditworthiness of the applicant for loan.

The third sub-question was: *What are the issues to be considered while developing and implementing the credit scoring models within new or emerging markets?*

In order to answer this question, an extensive discussion from the existing literature on the issues of model overrides, model validation and model performance have been presented in Chapter Two. However, the modelling issues in the literature reviews were discussed against the background of a long history of credit scoring in a developed consumer credit environment. In a new or emerging market, like the Nepalese banking sector which does not at the time of this research have any formal credit scoring models, it was important to explore the modelling issues from the perspective of the managerial decision making process- the credit officers as they were the key person making credit decisions.

From the findings of the expert interviews presented in Chapter Four, it could be inferred that the historical database of accepted as well as rejected applicants from a single time horizon and from population applying for the same credit product is essential in developing a robust credit scoring model. The historical database of the borrowers should include all the range of characteristics obtained from the application forms to be considered in the modelling process, this would enable the model to statistically select the characteristics which jointly provide a significant predictor of the loan quality. As there was no overrides data it is suggested that all overrides credit decision made should be maintained and built back for future model development purposes.

In a new or emerging market, the operational, technical, business and cultural issues should be considered with the implementation of the credit scoring models. The operational issues relate to the use of the model and it is imperative that the staff and the management of the bank understand the purpose of the model. Application scoring models should be used for making credit decisions on new applications and behavioural models to supervise existing borrowers for limit expansion or for marketing of new products. The technical issues relate to the development of proper infrastructure, maintenance of historical data and software needed to build a credit scoring model within the bank. The business issues relate to whether the soundness and safety of the banks could be achieved through the adoption of the quantitative credit decision models, which would send a positive impact in the banking sector. The cultural issues relate to making credit irrespective of race, colour, sex, religion, marital status, age or ethnic origin. Further, the models have to be validated so as to ensure that the model performance is compatible in meeting the business as well as the regulatory requirements. Thus, the above issues have to be considered while developing and implementing credit scoring models within a new or emerging markets.

The main research question was: *To what extent is the development of an objective credit scoring models achievable within the Nepalese banking sector?*

By answering the above three sub-questions, this research have presented a thorough examination of the issues relating to the development of an objective credit scoring models in the Nepalese banking sector. The sequential mixed methods approach comprising of preliminary study, expert interviews and the credit application forms as presented in Chapter Three has enabled to establish and confirm the characteristics to be considered in the model development process. The model development issues discussed within the literature and also as findings from the expert interviews guided and informed the research process. The final *"Credit Scoring Model"* presented in Chapter Four show that the development of an objective credit scoring models is achievable within the Nepalese banking sector.

5.3 Contributions of the Research:

With regard to the contributions of the research, Philips (1992, p. 128) states that *"contribution is something nobody has said before and/or carrying out empirical work that has not been done before"* whilst *Bourner et al.,* (2000, p. 494) assert, *"(DBA) is a program of research-based management development aimed at developing the capacity to make a significant original contribution to management practice"*. Reflecting on the above quotes it could be argued that the nature of DBA research is being able to make theoretical as well as practical contributions in solving real life problems of significance to business and management. In line with the argument, the different areas to which the present research has contributed both in theory and practice are discussed in the following paragraphs.

The main contribution of this research could be related to the point made by Philips (1992) which is embedded on the research topic "Consumer Credit Scoring- an empirical study involving home loans within the Nepalese banking sector" meaning that this study has carried out an empirical work that has not been done within the Nepalese banking sector. The choice of the research area is related to the growth of the consumer credit market (from the year 2002), the sparse literature on consumer credit risk management and non adoption of an objective risk rating technique on the lines of credit scoring within the Nepalese banking sector (Ramamurthy, 2004; Upadhyay, 2005; Nepal Rastra Bank, 2004). Though previous studies in the field of credit scoring had adopted a positivist paradigm (Henley, 1995; Kelly, 1998), the contribution of this study is that it combines the benefits of the positivist and interpretivist paradigms and adopts the pragmatist paradigm in which both the qualitative and quantitative methods are well-matched. Within the scope of the pragmatist paradigm a sequential mixed methods approach comprising of preliminary study, expert interviews and credit application forms was adopted. The mixed methods approach is also unique in the sense that the research questions were answered with academic rigour considering all aspects of credit decision making process.

Through the execution of the questionnaire survey which was targeted at the non-managerial level, an initial overview of consumer credit risk and the characteristics to be considered for assessing the creditworthiness of the applicant was established. Thereafter, the expert interviews conducted with the managerial level helped to explore the soft issues relating to consumer credit decision making and credit scoring modelling. This process enabled the researcher to obtain a holistic view which was instrumental in the next step of model development. By providing a different direction in terms of the research approach resulting in the empirical findings presented and discussed in Chapter Four this work makes a theoretical contribution to knowledge.

Relating to the above statement made by *Bourner et al.,* (2000), it is imperative to draw the research contribution to management practice. The unique value of this work is that it has included the views of both the managerial and the non-managerial staff involved in the credit decision process. From the preliminary study, it could be suggested that in terms of management practice, the consumer credit policy has to be distinct and different from the corporate credit policy. Such a distinction in the policy would enable banks to market the lending properly and also to allocate resources as in accordance with the risk appetite of the bank.

Another issue relevant to management practice is the important characteristics to be considered while assessing the applicant for credit. Evidence from the preliminary study and the expert interviews suggest that it is not always possible in practice to assess and evaluate all the applicant information from the credit application forms. From the preliminary study, it could be suggested that applicant age, collateral/guarantee and monthly income are the most important characteristics to be considered for assessing the creditworthiness of the applicant. However, the findings of the expert interviews suggest that in addition to these three characteristics a fourth one, type of employment is also important. However, when considered in the credit scoring model, these were not the characteristics found to be significant. The one consistent characteristic was the type of employment and others were the type of occupation, the purpose of the loan, the total cost of the project, the loan amount requested and finally, the stage of the project. Thus, on a practical level, the important characteristics to be considered in assessing the creditworthiness of the applicant and consumer credit decision making were identified.

Further, the issues on model development, model implementation and evaluation identified within the literature and found empirically in this study have identified the challenges banks in the new/emerging markets could encounter in the formal credit scoring model development process. This study offers banks in the new/emerging markets with a valuable insight on the operational, technical, cultural and business issues relating to credit scoring that will be faced in developing or adopting a credit scoring model in the future. Moreover, the practical relevance of this research with the Nepalese banking sector could be related to the comment made by one of the respondent in the expert interview who noted, *"I think the future of consumer lending would be based on credit scoring".* All the respondents also suggested that because of the market requirements, the banks will have to move towards adopting a combination of judgmental system alongside a credit scoring model to assist in credit decision making. This clearly demonstrates the practical contributions of this research.

The process of model development together with that was final model obtained as outcome of this study, has provided a valuable dimension not only to the Nepalese banks but also to model developers in the new/emerging markets as it provides details on appropriate modelling techniques, the sampling process, data considerations and performance monitoring. In response to the regulator of the Nepalese banking sector who has emphasised the need for risk-based supervision; Nepalese banks have to begin adopting more sophisticated risk based credit decision frameworks. It is argued that the credit scoring model developed here could be used as a prototype model for consumer credit in the Nepalese banking sector.

5.4 Implications for Professional Practice:

From the conception of this research and the research process, the findings offer a comprehensive review on the existing credit decision making framework in the Nepalese banking sector. With the growth of the consumer credit and the emphasis placed on risk management, it is becoming imperative for Nepalese banks to adopt an objective, fast and consistent credit decision making framework. The present credit decision making framework which is based on the judgmental approach is increasingly inappropriate for the large volume of applicants for consumer credit. This study offers Nepalese banks as well as banks in other new or emerging markets the opportunity to adopt a risk based statistical credit decision making framework on the lines of credit scoring.

In addition to the implications for the banks, this research also made practical implications for the regulators of the banking sector. Nepal Rastra Bank in its policy document has expressed its intention of adopting a risk based supervision framework and has emphasised that Nepalese banks should start working towards adoption of the Basel II Accord, requiring a risk-based approach towards loans and advances. This research would provide a valuable reference frame for the regulator for offering advice to Nepalese banks on how to adopt a risk-based customer rating model.

This research took a pragmatic approach by appreciating the value of both qualitative and quantitative aspects to model developing. Thus, from the professional practice point of view, the implication of this research on bankers, risk professionals and researchers is to consider a holistic approach while formulating decision support systems in solving real life problems in business and management.

5.5 Limitations of this Research and Recommendations for Future Research:

This study has achieved to develop a credit scoring model for the Nepalese banking sector. However, the conduct of the research had some limitations, which could be improved and can indicate directions for future research.

- Preliminary Study:

The section A of the questionnaire could have been improved by incorporating more than two categories as answers, or by applying open ended questions. The data was collected from non-managerial level staff from Nepalese banks based in the capital city, Kathmandu. By including respondents operating in other major Nepalese cities, would have enabled the collection of richer data that would have allowed for more advanced statistical tests could have been conducted to gain more perspective on the theme of the research.

- Expert Interviews:

The sample size was only five respondents from different Nepalese banks. More respondents would have allowed for greater generilisability of the findings. The interviews could also have included the regulator's perspective on the research theme. During the interviews process, digital recordings of the interviews were not allowed, which resulted in the interviewer to manually transcribe the responses. In this process, the interviewer might have missed important points that were communicated and also could not review the interviews. Finally, researcher biased in recording the findings cannot be ruled out.

- Credit Application Forms:

With regard to model development, sample size of the historical customer application forms the database was small when compared with samples taken in the other studies presented in Table 3.3. It is a small representation of the fast growing consumer credit market of the Nepalese banking industry. Though, the overall performance of the final model at 50% cut-off (presented in Equation 4.1) is satisfactory (83.70 per cent), when compared to other studies (as presented in Table 2.7). However, the percentage of correctly classified bad credits is 8.6 per cent is not satisfactory. Through the inclusion of more explanatory characteristics, large dataset containing equal sample of good as well as bad debts, this model could have been improved in correctly classifying bad credits. Macroeconomic characteristics such as inflation, economic growth were not built in the model, which is a major limitation. Other modelling techniques for example decision trees; neural networks could have been used if the sector had a history of credit scoring with mature data.

Further, the main constraints for model development would be to large database comprising of bank's customers as well as credit bureau data. This data should incorporate both rejected as well as accepted applicant so that a robust credit scoring model could be developed.

The limitations of this research and the outcomes that have emerged suggest a number of areas for future research:

- Extending this research to explore a larger sample size within the Nepalese banking sector or any other new/emerging markets.
- Comparing the results with the use of other modelling techniques would have enhanced the performance of the model.

- Model testing and calibrating it with the Basel II guidelines would make the model a robust risk based one, which the researcher would take up as post-doctoral work.
- Other areas such as risk pricing, behavioural scoring, fraud scoring could be explored within the Nepalese banking sector.

5.6 Personal Reflections:

"It is now widely accepted that successful professionals need to reflect upon their actions as most tasks are they perform involve novel elements to which there is no defined solutions" (Kember et al., 1999).

From the very inception of this DBA intellectual journey some four years ago, there have been period of ups and downs and I have been negotiating difficult times as well as enjoying good times during this period. Being a married person with family responsibilities, it was tough for me to be away for this period to pursue my aspiration for a doctoral qualification. After successfully completing all the course work of the taught component and having written the thesis for the research component, it is time for me to put my personal reflections on the research journey.

The first requisite before taking any work is to have the proper tools and the right skills to use these tools and the key challenge for me was to acquire the research skills. The taught component of the DBA programme was conducted over a period of four years with eight blocks of teaching and training session covering areas such as business research projects, research philosophies, business research methods, and personal and professional development. Besides mastering the qualitative and quantitative techniques, I have learned how to use SPSS, NVivo, Endnote and Turnitin to assist my research process. As part of the business research projects, I had to undertake small projects and use the research knowledge and skills to develop my understanding of the research process. Critical thinking and critiquing others work was a major asset I acquired through the taught programme which has made been instrumental in generating new ideas and ways of dealing with situations.

As Phillips and Pugh (1994) writes *"....you are not doing research in order to do research, you are doing research in order to demonstrate that you have learned how to do research to fully professional standards".* This implies that through the research process, I have been developing myself into the field of research and aspiring to join the community of active researchers in future. In meeting this, I had fully engaged myself during this research journey by presenting and discussing the research findings in academic as well as practitioners' conferences. Mention may be made of the 10th Credit Scoring and Credit Control Conference which I attended with my supervisor. This conference helped me in formulating the research approach and also networking with other researchers in the area of credit scoring and credit control. Thereafter, I participated in the 1st European Risk Management Conference which was also helpful getting valuable comments on my research findings and the future directions of the work. Thus, I am in the process of formally joining the community of researchers after the successful completion of my doctoral journey.

With regard to personal development, the comprehensive understanding of the financial risk management subject area from the practical as well as academic standpoint has reshaped my career prospects towards being an academic consultant. I would like to see myself working to solve real life business and management problems through academic setting and rigour. This research is an example of how theory could be used into practice. As part of my future plans, I would like to test the credit scoring model developed and also move forward in providing consultancy to banks and financial institutions in the areas of risk management.

5.7 Chapter Summary:

To summarise, this chapter has presented the discussion of the findings with reference to the research questions, the contributions made by the research as well as its professional implications. The limitations of the research and recommendations for future research have been discussed. Further, discussion was rooted to the demand of the market and the business needs of the Nepalese banks to determine the best method/way to assess the creditworthiness of the applicant. Though applicant age, type of employment, collateral/guarantee and monthly income was suggested to be the factor/characteristics considered important, but it could be argued that the method of assessment determines which factor/characteristics to be considered. There are operational, cultural, businesses, technical issues which the model developers have to take into consideration during model development process. Thus, the main research question has been answered by developing the credit scoring model. Finally, the limitations of the research in terms of data collection procedure, questionnaire design, sample size and modelling considerations along with directions for possible future research have been discussed. Finally, this research journey has been instrumental in shaping the career prospects of the researcher.

Appendix A: Philosophical paradigms underpinning this research:

Kuhn (1970) coined the term *"paradigm meaning a set of beliefs, values, and assumptions that a community of researchers has in common regarding the nature and conduct of research. The beliefs include, but are not limited to, ontological beliefs, epistemological beliefs, axiological beliefs, aesthetic beliefs and methodological beliefs"* (Kuhn, 1970). In research practice, a paradigm provides guidelines about how a researcher should conduct a study to answer the research question by specifying the most appropriate research methods (Morgan, 1998). Philosophically, researchers make claims about what is knowledge (ontology), how we know it (epistemology), what values go into it (axiology), and the processes for studying it (methodology) (Creswell, 2003). In short, a paradigm refers to a research culture (Patton, 1990). It is the philosophical paradigm which guides the research process. "*Failure to think through philosophical issues such as this, while not necessarily fatal, can seriously affect the quality of management research, as they are central to the notion of research design*" (Easterby-Smith *et al.*, 2002, p. 27).

Easterby-Smith *et al.*, (2002) supplements this view by identifying three reasons as to why understanding philosophical paradigms may be significant:

- *"Firstly, it can help the researcher to refine and specify the research methods which will be used in the study. This would involve the type of data gathered and its origin, the way in which such data is interpreted and how it helps to answer the research questions".*
- *"Secondly, knowledge of the philosophy will assist the researcher to reflect and consider different methodologies and methods thereby avoiding the inappropriate use of a particular approach at an early stage".*
- *"Thirdly, it may facilitate the researcher towards an innovative, creative approach to research".*

According to Morgan (1998), research methods can be considered, classified and described at different levels, the most basic of which is the philosophical level. Within the research traditions, two views about philosophy dominate the literature: Positivist and Interpretivist (Lincoln and Guba, 1985; Bryman, 2004; Easterby-Smith *et al.*, 2002).

Positivist Paradigm:

Positivism adopts the philosophical stance of a natural scientist and considers that the social world exists externally and its properties should be measured objectively (Easterby-Smith *et al.*, 2002; Saunders *et al.*, 2005). Crotty (1998) highlighted that Auguste Comte, the French philosopher was the first person to formulate the positivistic view as he said:

"All good intellects have repeated, since Bacon's time, that there can be no real knowledge but that which is based on observed facts" (Comte, 1853) Cited in Crotty (1998, p. 20).

Ontologically, the above statement given by Comte (1853) reflects that reality is external and objective; epistemologically, knowledge is only significant if it is based on observation of the external reality. Crotty (1998, p.20) explains that *"what is posited or given in direct experience is what is observed, the observation in question being scientific observation carried out by way of the scientific method"*. Smith (1998) complements Comte's view by stressing that social sciences phenomena could be studied as hard facts and the relationship between these facts can be established as scientific laws.

Positivists maintain that social science inquest should be objective, making detached interpretations. They also assume reality is unitary and it can be understood by empirical and analytic method (Smith, 2003). This approach presumes to prevent individuals' values and biases from influencing outcomes (Guba and Lincoln, 1994) emphasising a highly structured methodology to facilitate replication (Gill and Johnson, 2002). Positivism is a process of arriving at research conclusions through an organised and convincing process and not merely by assumptions. Popper (1965) has commented that the propositions making up a scientific theory need to satisfy four conditions: *"they must exhibit internal consistency, they must be empirically testable, they must survive attempts at empirical testing, and they must be at least as explanatory or predictive as any rival theory"*. Thus, *"a positivist approach would follow the methods of the natural sciences and, by way of allegedly value-free, detached observation, seek to identify universal features of humanhood, society and history that offer explanation and hence control and predictability"* (Crotty, 1998, p.67).

<u>Interpretivist Paradigm:</u>

In contrast to the positivist paradigm presented above, an interpretivist approach, *"looks for culturally derived and historically situated interpretations of the social life-world"* (Crotty, 1998, p.7). The interpretivist considers that the social world exists internally and its properties should be measured subjectively (Easterby-Smith, *et al.,* 2002). From an interpretivist point of view, to understand a particular social action, meaning in an action must be found and interpreted, and constructed afterwards (Guba and Lincoln, 1994; Saunders *et al.,* 2005).

The interpretivist conceives of a world where there is no single reality, but multiple realities exist and these are formed in the minds of individuals. They hold that the researcher is not independent from the subject of study, but is a 'passionate participant' who interacts with the respondents to construct the outcome (Guba and Lincoln, 1994). Hence, the outcome of the inquiry is constructed through the joint effort of the researcher and the respondents during the process (Bryman, 2004).

Pragmatist Paradigm:

Increasingly, authors and researchers in business research argue that one should attempt to mix approaches to some extent, because it provides more perspectives on the phenomena being investigated (Abrahamson, 1983; Easterby-Smith *et al.,* 2002; Creswell, 2003). Philosophically, while attempting to establish a link between the positivist and the interpretivist paradigms discussed earlier in this Chapter, Howe (1988) suggested a paradigm named "pragmatism" which embraces the use of both the quantitative and qualitative methods.

This view is supported by Brewer and Hunter (1989, p.74) by adding that:

"the pragmatism of employing multiple research methods was used to study the same pragmatic implications for social theory. Rather than being wed to a particular theoretical style and its most compatible method, one might instead combine methods that would encourage or even require integration of different theoretical perspectives to interpret the data."

A pragmatist uses simply "*what works*" (Howe, 1988) and shares concern from both the positivist and interpretivist paradigm (Goldkuhl, 2004). The decision on the use of either the quantitative or qualitative methods (or both) depends on the research questions. The major elements of the three philosophical paradigms are summarised as in the table below.

Summary of the Philosophical Paradigms

Paradigm	**Positivist**	**Interpretivist**	**Pragmatism**
Methods	Quantitative	Qualitative	Quantitative + Qualitative
Logic	Deductive	Inductive	Deductive + Inductive
Epistemology	Objective point of view, knower and known are dualistic.	Subjective point of view, knower and known are inseparable.	Both objective and subjective points of view
Axiology	Inquiry is value-free	Inquiry is value-bound	Values play a large role in interpreting results
Ontology	Naive realism	Relativism	Accept external reality. Choose explanations that best produce desired outcomes
Causal Linkages	Real cause's provisionally precedent to or simultaneous with effects.	All entities simultaneously shape each other. It's impossible to distinguish causes from effects.	There may be causal relationship but cannot be pinned down.

(Source: Adapted from Tashakkori and Teddlie (1998) Mixed Methodology: Combining Qualitative and Quantitative Approaches, p.23)

The pragmatists believe that through the use of a mixed methodological approach, a better understanding of the research problem could be achieved in the realm of business research (Brewer and Hunter, 1989; Tashakkori and Teddlie, 1998; Easterby-Smith *et al.,* 2002; Creswell, 2003). Moreover, pragmatism is an appropriate paradigm when it is deemed necessary to integrate building theory and theory testing which can overcome the problems of complexities when the literature is sparse in the context of the research (Tashakkori and Teddlie, 1998; Creswell, 2003).

Appendix B: Preliminary Study

B1- Introduction Letter
B2- Questionnaire
B3- Frequency Distribution of Section A
B4- Correlation Matrix
B5- KMO and Bartlett's Test
B6- Total Variance Explained (using PCA)
B7- Monte Carlo PCA for Parallel Analysis
B8- Component Matrix
B9- Component Score Covariance Matrix
B10- Total Variance
B11- Rotated Component Matrix

B1- Introduction Letter

NB 317, Northumberland Building,
Newcastle Business School,
Northumbria University,
Newcastle upon Tyne,
United Kingdom.

Dear Sir/Madam,

I am conducting a study on the "Consumer Credit Risk". I am particularly interested in the issues and implications with regard to home loan. This study is one of the requirements of a course on Advanced Business Research Methods (ABRM), which I am taking as part of my Doctorate Degree in Business Administration. The purpose of this study is the use research methods so as to fit in my doctoral thesis.

Towards that end, I am requesting you to complete the attached questionnaire. Your responses to these questions will help me understand your views on consumer credit risk management.

All information you provide will be treated in a confidential manner and neither you nor the name of your bank will be identified in the final paper that I will write for this course.

Thank you very much for your time and consideration.

Yours truly,

(Satish Sharma)

satish.sharma@unn.ac.uk

B2- Questionnaire:

Consumer Credit Risk: Issues and Implications with regard to Home Loan.

Section A: Please tick the appropriate answer.

1. Does your bank have a Consumer Credit Policy?	Yes	No
2. Is the Policy different from Corporate Credit Policy?	Yes	No
3. Does the Policy define hierarchy and authority?	Yes	No
4. Does the banking culture determine the rate and means by which Credit Policy alters?	Yes	No
5. Are the Credit decisions based on the profitability profiles, rather than the risk profiles?	Yes	No
6. Do you price the credit according to the risk profile of the applicant?	Yes	No
7. Do you think that adequate collateral/guarantor minimises credit risk?	Yes	No
8. Does your bank have a risk management department?	Yes	No
9. Have you been trained in the areas of risk management?	Yes	No
10. Is credit information from Credit Information Bureau (CIB) a mandatory part in Consumer Credit decisions?	Yes	No

Section B: While assessing the applicant's application for Home Loan, what weightage do you give to the following variables? (Please tick the appropriate)

Variables	Very Important	Important	Moderately Important	Of little Importance	Unimportant
11. Applicant Age	1	2	3	4	5
12. Marital Status	1	2	3	4	5
13. No. of Dependents	1	2	3	4	5
14. Employment Status	1	2	3	4	5
15. Years of Employment	1	2	3	4	5
16. Total Assets	1	2	3	4	5
17. Monthly Income	1	2	3	4	5
18. Monthly Expenditure	1	2	3	4	5
19. Property Value	1	2	3	4	5
20. Property Location	1	2	3	4	5
21.Loan to Value Ratio	1	2	3	4	5
22. Loans Defaulted	1	2	3	4	5
23. Collateral/Guarantee	1	2	3	4	5

Thank you for completing this questionnaire. Anonymity is assured and your responses will be used purely for academic purposes.

B3- Frequency Distribution of Section A

Questions	Yes	No
1. Does your bank have a Consumer Credit Policy?	65.3%	34.7%
2. Is the Policy different from Corporate Credit Policy?	41.7%	58.3%
3. Does the Policy define hierarchy and authority?	80%	20%
4. Does the banking culture determine the rate and means by which Credit Policy alters?	63%	37%
5. Are the Credit decisions based on the profitability profiles, rather than the risk profiles?	100%	-
6. Do you price the credit according to the risk profile of the applicant?	-	100%
7. Do you think that adequate collateral/guarantor minimises credit risk?	90%	10%
8. Does your bank have a risk management department?	40.28%	59.72%
9. Have you been trained in the areas of risk management?	32.86%	67.14%
10. Is credit information from Credit Information Bureau (CIB) a mandatory part in Consumer Credit decisions?	100%	-

B4- Correlation Matrix:

		Applicant Age	Marital Status	No. of Dependents	Employment Status	Years of Employment	Total Assets	Monthly Income	Monthly Expenditure	Property Value	Property Location	Loan to Value Ratio	Loans Defaulted	Collateral/ Guarantee
Applicant Age	Pearson Correlation	1	.865(**)	.838(**)	.609(**)	.447(**)	.265(*)	-.005	.227	.092	.261(*)	-.092	.075	-.085
	Sig. (2-tailed)	.	.000	.000	.000	.000	.025	.967	.055	.441	.027	.440	.533	.480
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Marital Status	Pearson Correlation	.865(**)	1	.863(**)	.507(**)	.358(**)	.164	-.064	.230	-.006	.308(**)	-.179	.027	-.147
	Sig. (2-tailed)	.000	.	.000	.000	.002	.172	.592	.052	.957	.008	.133	.819	.219
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
No. of Dependents	Pearson Correlation	.838(**)	.863(**)	1	.498(**)	.390(**)	.211	-.097	.255(*)	-.047	.366(**)	-.127	.110	-.069
	Sig. (2-tailed)	.000	.000	.	.000	.001	.077	.419	.031	.696	.002	.286	.356	.566
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Employment Status	Pearson Correlation	.609(**)	.507(**)	.498(**)	1	.659(**)	.347(**)	.070	.312(**)	.182	.184	-.007	.007	.042
	Sig. (2-tailed)	.000	.000	.000	.	.000	.003	.560	.008	.126	.123	.954	.952	.723
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Years of Employment	Pearson Correlation	.447(**)	.358(**)	.390(**)	.659(**)	1	.251(*)	-.023	.342(**)	.182	.117	.050	.149	.118
	Sig. (2-tailed)	.000	.002	.001	.000	.	.035	.850	.003	.126	.326	.677	.211	.325
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Total Assets	Pearson Correlation	.265(*)	.164	.211	.347(**)	.251(*)	1	-.105	.067	.305(**)	-.016	.057	-.015	-.068
	Sig. (2-tailed)	.025	.172	.077	.003	.035	.	.384	.581	.010	.898	.639	.899	.574
	N	71	71	71	71	71	71	71	71	71	71	71	71	71
Monthly Income	Pearson Correlation	-.005	-.064	-.097	.070	-.023	-.105	1	-.003	-.116	.069	-.040	-.023	.164
	Sig. (2-tailed)	.967	.592	.419	.560	.850	.384	.	.979	.332	.567	.741	.846	.168
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Monthly Expenditure	Pearson Correlation	.227	.230	.255(*)	.312(**)	.342(**)	.067	-.003	1	.011	.264(*)	.045	.087	.248(*)
	Sig. (2-tailed)	.055	.052	.031	.008	.003	.581	.979	.	.927	.025	.709	.467	.036
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Property Value	Pearson Correlation	.092	-.006	-.047	.182	.182	.305(**)	-.116	.011	1	-.017	.534(**)	.309(**)	.366(**)
	Sig. (2-tailed)	.441	.957	.696	.126	.126	.010	.332	.927	.	.886	.000	.008	.002
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Property Location	Pearson Correlation	.261(*)	.308(**)	.366(**)	.184	.117	-.016	.069	.264(*)	-.017	1	-.116	.025	.099
	Sig. (2-tailed)	.027	.008	.002	.123	.326	.898	.567	.025	.886	.	.332	.834	.410
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Loan to Value Ratio	Pearson Correlation	-.092	-.179	-.127	-.007	.050	.057	-.040	.045	.534(**)	-.116	1	.409(**)	.656(**)
	Sig. (2-tailed)	.440	.133	.286	.954	.677	.639	.741	.709	.000	.332	.	.000	.000
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Loans Defaulted	Pearson Correlation	.075	.027	.110	.007	.149	-.015	-.023	.087	.309(**)	.025	.409(**)	1	.521(**)
	Sig. (2-tailed)	.533	.819	.356	.952	.211	.899	.846	.467	.008	.834	.000	.	.000
	N	72	72	72	72	72	71	72	72	72	72	72	72	72
Collateral/Guarantee	Pearson Correlation	-.085	-.147	-.069	.042	.118	-.068	.164	.248(*)	.366(**)	.099	.656(**)	.521(**)	1
	Sig. (2-tailed)	.480	.219	.566	.723	.325	.574	.168	.036	.002	.410	.000	.000	.
	N	72	72	72	72	72	71	72	72	72	72	72	72	72

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

B5- KMO and Bartlett's Test:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.742
Bartlett's Test of Sphericity	Approx.Chi-Square	416.145
	df	78
	Sig.	.000

B6- Total Variance Explained (using PCA):

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.862	29.704	29.704	3.862	29.704	29.704
2	2.520	19.382	49.087	2.520	19.382	49.087
3	1.383	10.637	59.724	1.383	10.637	59.724
4	1.098	8.445	68.169	1.098	8.445	68.169
5	.942	7.244	75.413			
6	.819	6.302	81.715			
7	.602	4.633	86.349			
8	.591	4.543	90.891			
9	.426	3.277	94.168			
10	.284	2.185	96.354			
11	.237	1.822	98.176			
12	.124	.955	99.130			
13	.113	.870	100.000			

B7 - Monte Carlo PCA for Parallel Analysis:

Eigenvalue	Random Eigenvalue	Standard Deviation
1	1.6432	0.1029
2	1.4827	0.0682
3	1.3526	0.0505
4	1.2426	0.0546
5	1.1378	0.0450
6	1.0491	0.0418
7	0.9610	0.0394
8	0.8853	0.0365
9	0.8103	0.0429
10	0.7315	0.0413
11	0.6546	0.0390
12	0.5820	0.0397
13	0.4864	0.0481

(Source: Watkins, M.W. (2000) Monte Carlo PCA for Parallel Analysis (computer software). State College, PA: Ed& Psych Associates)

B8- Component Matrix

	Component			
	1	2	3	4
Applicant Age	.897	-.113		-.164
No. of Dependents	.870	-.162		-.308
Marital Status	.858	-.226		-.283
Employment Status	.774		-.134	.392
Years of Employment	.661	.202	-.106	.376
Monthly Expenditure	.431	.182	.360	.284
Loan to Value Ratio		.848		-.112
Collateral/Guarantee		.835	.356	
Property Value	.148	.691	-.399	
Loans Defaulted	.126	.662	.181	-.352
Total Assets	.371	.118	-.629	.247
Property Location	.402		.511	-.102
Monthly Income			.482	.557

Extraction Method: Principal Component Analysis.
4 components extracted.

B9- Component Score Covariance Matrix

Component	1	2	3	4
1	1.000	.000	.000	.000
2	.000	1.000	.000	.000
3	.000	.000	1.000	.000
4	.000	.000	.000	1.000

Extraction Method: Principal Component Analysis.
Component Scores.

B10- Total Variance

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	3.852	29.630	29.630
2	2.514	19.336	48.966
3	1.399	10.759	59.724

Extraction Method: Principal Component Analysis.

B11- Rotated Component Matrix

	Component		
	1	2	3
Applicant Age	.900		
No. of Dependents	.881		
Marital Status	.871		
Employment Status	.761		
Years of Employment	.642		
Monthly Expenditure	.435		.320
Collateral/Guarantee		.864	
Loan to Value Ratio		.833	
Loans Defaulted		.682	
Property Value		.657	-.468
Total Assets	.335		-.655
Property Location	.427		.494
Monthly Income			.480

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

Appendix C: Expert Interviews

C1- Introduction Letter
C2 -Expert Interviews Guide
C3-Informed Consent Form
C4- Expert Interview Guide (Prior and after the piloting process)
C5- Matrix Analysis of Expert Interviews

C1- Introduction Letter

NB 317, Northumberland Building,
Newcastle Business School,
Northumbria University,
Newcastle upon Tyne,
United Kingdom.

Dear Sir/Madam

Further to our telephone conversation, I would like to thank you for agreeing to take part in the interview process in spite of your busy schedule.

The interview is focussed on the area of "consumer credit". And I am particularly interested to explore and understand the current consumer credit decision making process within the Nepalese banking sector. This would help me to explore the softer issues relating to customer data and information handling, credit scoring model development, model implementation, model evaluation and performance from your perspective. The views and expert opinions given by you would help me to guide my research towards developing a credit scoring model for the Nepalese banking sector.

All information provided by you during the interview process would be treated as highly confidential and neither you nor your bank would be identified in the research process and in the final thesis that I would write. Please find herewith the interview guide and the informed consent form for your reference.

Once again, thank you very much for your time and consideration.

Sincerely Yours,

(Satish Sharma)

satish.sharma@unn.ac.uk

C2 -Expert Interviews Guide

Section A: The Credit Decision Process

1. How would you describe the current consumer credit decision process within your bank?

2. To what extent do you and your colleagues in the credit department understand the various credit modelling techniques?

3. Is your credit decision based on judgmental or quantitative evaluation methods? If judgmental methods are applied, how do you maintain consistency along all credit decision?

4. Are you using quantitative evaluation method as a tool for formal credit granting decisions in your organisation? If yes, did you develop it in-house or purchase from an outside provider? If no, do you intend to outsource model development in the future?

5. What role do you think credit scoring would play in your credit granting decision processes?

Section B: Data Handling and Analysis

1. To what extent can you rely upon the accuracy and completeness of customer data from sources internal to your bank?

2. To what extent can you rely upon the accuracy and completeness of customer data from sources external to your bank?

3. To what extent does the verification of the data on the customer application forms affect the credit decision process? What do you do for the missing information?

4. Are there any specific (not provided) application responses that are significant in affecting the decision process within your bank?

5. What steps, if any, does your bank take to evaluate the accuracy and honesty of the information provided by customers on their application for credit?

6. Does your bank make use of the credit information bureau report? Or credit reference or inter-bank reference?

If relevant, how reliable do you consider it to be? Does this report/reference play an important part in the credit decision process?

Section C: Model Development

1. Can you describe how your bank has used or intends to use historic data in the development of credit scoring models? Will this involve data from accepted customers, rejected applications, and/or accepted customers only with known outcomes?

2. Is the process of augmentation (reject inference) important while developing the model? How do you incorporate this in your model development?

3. What range of variables/factors do you anticipate any formal model will consider, and in turn, include?

4. What internal and external variables/factors would you most likely consider as potential predictors of loan success/default?

5. Are there any potential problems relating to scoring errors?

6. If there were any overrides in the credit decision process, would the overrides data be analysed and built back into the model? If so, how

Section D: Implementation Issues

1. With whom will responsibility lie for the operational implementation of credit decision models in the front line of your business?

2. What are the technical issues associated with the implementation of a quantitative credit decision models?

3. What are the business issues associated with the implementation of a quantitative credit decision models?

4. What are the cultural issues associated with the implementation of a quantitative credit decision models?

5. To what extent, if any, can those implementing the model override the model's decisions? Who triggers this override process?

6. What levels of overrides do you anticipate taking place in terms of percentage of decisions? Do overrides go in both directions?

Section E: Model Evaluation and Performance

1. Is your bank likely to adopt a combination of judgmental/quantitative approaches to credit scoring?

2. If you choose to rely exclusively on your credit scoring models, will you undertake the assessment of any qualitative risk (sample customers perhaps)?

3. How often do you anticipate the validation of your credit scoring models?

4. What performance criteria will you use to determine this?

5. To what extent will the customers be aware of the performance criteria? For example, will mechanisms be put in place for them to provide feedback?

6. Does behavioural scoring help to reset the credit performance criteria in mortgage lending? If yes, how would you incorporate the changes?

7. How long do you expect a scoring system to remain operational within your bank before updates take place and what performance criteria do you use or expect to use to indicate its time for replacement?

8. What would you anticipate the size and complexity of any credit scoring model to be in terms of number of factors measured and scored?

9. How would you monitor over time the current level of customer evaluation by your bank, in terms of good decisions made for accepted loans?

C3-Informed Consent Form

PARTICIPANT INFORMED CONSENT RECORD SHEET

northumbria
UNIVERSITY
Newcastle Business School

Dear Participant,

Thank you for agreeing to be a participant in this research.

You have been provided with an outline of the purpose and nature of this research project in the information letter that you were sent recently. This form is being used to record that you have been fully *informed* about the research you are to be involved with and that you *consent* to taking part.

By signing below, you confirm that you understand the purpose of the study, have been given the opportunity to ask questions regarding the study and that you agree to being interviewed and recorded.

Please remember that you may decline to answer any questions and may withdraw at any stage. Also, all personal details will be kept completely confidential and will not appear in any printed material.

Please sign below to indicate your agreement:

Name (BLOCK CAPITALS) ....

Signature..

Date..

The lead researcher for this project is:

Satish Sharma
Room 317, Northumberland Building,
Newcastle Business School,
Northumbria University,
NE1 8ST
Tel: 0044-191-2273038Email: satish.sharma@unn.ac.uk

A copy of this form will be returned to you.

Please note: The University is the Data Controller under the Data Protection Act.

C4- Expert Interview Guide (Prior and after the piloting process)

Questions Prior to Piloting Process	Questions After Piloting Process
1. The Process: Will you describe the retail credit decision process within your bank? What is the role of formal credit scoring in the credit granting decision by your organisation? **2. Data Handling and Analysis:** To what extent can you rely upon the accuracy and completeness of customer data, data sources internal to your bank? To what extent can you rely upon the accuracy and completeness of customer data, data sources external to your bank? To what extent does the completeness of otherwise of customer application forms affect the credit decision process? Are there any specific non-standard application responses that are significant in affecting this decision process? What steps, if any, does your bank take to evaluate the accuracy and honesty of the information provided by customers on their application for credit? How, if at all, does your bank make use of the credit bureau report? If relevant, how do reliable! Do you consider it to be? To what extent do you and your colleagues in the credit lending area understand the various methods of credit scoring and decision? Can you describe what you mean by the terms quantitative and judgmental? Can you describe how your bank has used or intends to use historic data in the development of credit scoring models? Will this involve data from accepted customers, rejected applications, and/or accepted customers only with known outcomes? Is the process of augmentation (reject inference) important while developing the model? What range of variables do you anticipate any formal model will consider, and in turn, include? What factors would you most likely consider as potential predictors of mortgage loan success/default? What would you anticipate the size and complexity of any credit scoring model to be in terms of number of factors measured and scored? How would you assess the current level of customer evaluation by your bank, in terms of good decisions made for accepted loans? Are there any potential problems relating to scoring errors? **3. Implementation Issues:**	**Section A: The Credit Decision Process** 1. How would you describe the current consumer credit decision process within your bank? 2. To what extent do you and your colleagues in the credit department understand the various credit modelling techniques? 3. Is your credit decision based on judgmental or quantitative evaluation methods? If judgmental methods are applied, how do you maintain consistency along all credit decision? 4. Are you using quantitative evaluation method as a tool for formal credit granting decisions in your organisation? If yes, did you develop it in-house or purchase from an outside provider? If no, do you intend to outsource model development in the future? 5. What role do you think credit scoring would play in your credit granting decision processes? **Section B: Data Handling and Analysis** 1. To what extent can you rely upon the accuracy and completeness of customer data from sources internal to your bank? 2. To what extent can you rely upon the accuracy and completeness of customer data from sources external to your bank? 3. To what extent does the verification of the data on the customer application forms affect the credit decision process? What do you do for the missing information? 4. Are there any specific (not provided) application responses that are significant in affecting the decision process within your bank? 5. What steps, if any, does your bank take to evaluate the accuracy and honesty of the information provided by customers on their application for credit? 6. Does your bank make use of the credit information bureau report? Or credit reference or inter-bank reference? If relevant, how reliable do you consider it to be? Does this report/reference play an important part in the credit decision process? **Section C: Model Development** 1. Can you describe how your bank has used or intends to use historic data in the development of credit scoring models? Will this involve data

With whom will responsibility lie for the operational implementation of models in the front line of your business? To what extent, if any, can those implementing the model override the model's decisions? Who triggers this override process? What levels of overrides do you anticipate taking place in terms of percentage of decisions? Will the overrides data be analysed and built back into the model? **<u>4. Model Evaluation:</u>** To what extent, if any, will your bank evaluate any credit scoring model against qualitative risk? Is your bank likely to adopt a combination of judgmental/quantitative approaches to credit scoring? If you choose to rely exclusively on your credit scoring models, will you undertake the assessment of any qualitative risk (sample customers perhaps)? How often do you anticipate the validation of your credit scoring models? What performance criteria will you use to determine this? To what extent will the customers be aware of the performance criteria? For example, will mechanisms be put in place for them to provide feedback? Does behavioural scoring help to reset the credit performance criteria in mortgage lending? If yes, how would you incorporate the changes? How long do you expect a scoring system to remain operational within your bank before updates take place and what performance criteria do you use or expect to use to indicate its time for replacement?	from accepted customers, rejected applications, and/or accepted customers only with known outcomes? 2. Is the process of augmentation (reject inference) important while developing the model? How do you incorporate this in your model development? 3. What range of variables/factors do you anticipate any formal model will consider, and in turn, include? 4. What <u>internal</u> and <u>external</u> variables/factors would you most likely consider as potential predictors of loan success/default? 5. Are there any potential problems relating to scoring errors? 6. If there were any overrides in the credit decision process, would the overrides data be analysed and built back into the model? If so, how **<u>Section D: Implementation Issues</u>** 1. With whom will responsibility lay for the operational implementation of credit decision models in the front line of your business? 2. What are the technical issues associated with the implementation of a quantitative credit decision models? 3. What are the business issues associated with the implementation of a quantitative credit decision models? 4. What are the cultural issues associated with the implementation of a quantitative credit decision models? 5. To what extent, if any, can those implementing the model override the model's decisions? Who triggers this override process? 6. What levels of overrides do you anticipate taking place in terms of percentage of decisions? Do overrides go in both directions? **<u>Section E: Model Evaluation and Performance</u>** 1. Is your bank likely to adopt a combination of judgmental/quantitative approaches to credit scoring? 2. If you choose to rely exclusively on your credit scoring models, will you undertake the assessment of any qualitative risk (sample customers perhaps)? 3. How often do you anticipate the validation of

	your credit scoring models? 4. What performance criteria will you use to determine this? 5. To what extent will the customers be aware of the performance criteria? For example, will mechanisms be put in place for them to provide feedback? 6. Does behavioural scoring help to reset the credit performance criteria in mortgage lending? If yes, how would you incorporate the changes? 7. How long do you expect a scoring system to remain operational within your bank before updates take place and what performance criteria do you use or expect to use to indicate its time for replacement? 8. What would you anticipate the size and complexity of any credit scoring model to be in terms of number of factors measured and scored? 9. How would you monitor over time the current level of customer evaluation by your bank, in terms of good decisions made for accepted loans?

C5- Matrix Analysis of Expert Interviews

Consumer Credit Risk: Issues and Implications with regard to Home Loan

Section A: The Credit Decision Process

1. How would you describe the current consumer credit decision process within your bank?

Bank A	**Bank B**	**Bank C**	**Bank D**	**Bank E**	**Major themes**
The marketing department produces a product paper after receiving the application from the applicant. The product paper contains the gist of the proposal, which is screened by the credit control officer for the risk and return trade off, and then it is put forward for necessary action to the higher manager for approval/rejection. If the product paper is accepted, then it is send to the legal department for screening and review. If the legal department gives a green signal then the credit is granted.	In terms of consumer credit, most of the application comes from cross selling of other products and from staff reference. After receiving the application, a proposal summary mutually signed by the credit assistant, credit officer and the branch manager is send to the corporate credit manager/ deputy general manager in Head Office for approval/ rejection. If approved, the legal required is made at the branch level, by transferring the collateral in the name of the Bank and then securing guarantee on the loan. We also have the retail lending manual through which we match the terms and conditions.	The application once received by the consumer banking division is converted into a product document as per the requirement of the internal product document draft (PDD) which is send to the legal department, the credit assessment department for necessary review and action. After receiving the comments from the concerned department, a visit is made by the staff of the sales department to the property of the applicant. After the review of the property, further recommendation is made. Based on recommendations on the product document, the credit manager approves/rejects the application.	All our credit application goes through the classic credit analysis process. This is an expert system wherein the five Cs of credit- character, capital, capacity, conditions and collateral of the applicant is analysed. The application is analysed against the five variables with reference to the set internal bank credit policy. If the applicant satisfies the criteria, then the application is processed further to the legal and credit risk assessment departments. If the file is given green signal, then the credit is granted.	At the heart of the credit decision process lies the screening of the application by the relationship officer. The application is screened with regard to the credit policy of the bank. Then it is send to the risk assessment officer for credit appraisal based on internally developed risk assessment matrix model. If the application satisfies the reference point in the model, then the application is send to the credit manager for approval. After, approval, it is send to the legal department for necessary documentation of the legal documents.	In house judgmental credit decision/risk assessment model similar to judgmental scorecard.

2. To what extent do you and your colleagues in the credit department understand the various credit modelling techniques?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
We are working in the direction through KYC and ALM. Recently we have also approved the credit policy.	No, we are not exposed to credit modelling techniques. However, there have been some training courses in credit risk management recently.	We have a SCB group credit models for screening of credit cards application. As per the country's requirement fairly good knowledge of credit and credit decision process.	Yes, credit modelling techniques are easy to use and the standard of credit decision is maintained. All our lending managers are required to undergo credit specific training and acquire international accreditation on credit skills.	We have the in house risk assessment matrix model.	In house risk assessment matrix model. Credit scoring not used.

3. Is your credit decision based on judgmental or quantitative evaluation methods?
If judgmental methods are applied, how do you maintain consistency along all credit decision?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Judgmental. It varies in pricing loan.	Judgmental. But for consistency we verify information through physical and cross verification.	100% Judgmental, but in line with the PDD.	Both. Our credit decision is value driven that represents a key element of a uniform, constructive and risk aware credit culture throughout the organisation.	Both. Quantitative support credit decision.	Credit decision based on judgmental evaluation

4. Are you using quantitative evaluation method as a tool for formal credit granting decisions in your organisation? If yes, did you develop it in-house or purchase from an outside provider? If no, do you intend to outsource model development in the future?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes, Consumer Lending is a new area in Nepal.	No. With growing consumer lending we might develop/outsource a model in future.	No. But we would need expertise for future development. Financial and business viability is important in having a model.	No. We are in the process of developing one in house. The eternal quest for better risk management continues with development and use of various tools and techniques to properly identify, assess, structure, mitigate risk.	Yes In- house development.	Quantitative evaluation techniques are not used at present. However, with the growth of consumer credit, the banks are of the view that they might need to develop/outsource a model in future.

5. What role do you think credit scoring would play in your credit granting decision processes?

Bank A	Bank B	Bank C	Bank D	Bank E	Major Themes
Credit scoring would play a vital role in initial credit screening.	Yes, I think the future of consumer lending would be based on credit scoring.	Before deciding on the credit scoring, it is important to consider the cost. But it will come in the near future. Three generation data is also needed to make it work.	Definitely, a very positive role in application screening and pricing of loans.	It would play an important role in years to come because till of today much of the decision is very much judgmental.	There was 100% consensus that credit scoring would play a vital role in future in terms of application screening and pricing of loans.

Section B: Data Handling and Analysis

1. To what extent can you rely upon the accuracy and completeness of customer data from sources internal to your bank?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
In terms of salaried individuals, the bank statement , cash flow, salary/rental and also the repayment sources (mixed)	It depends on the perception of the credit officer.	No formal way of verification. Trust. Audited balance sheet.	We have internal auditors who verify the data in respect of the customer.	Assigned valuators. Credit control judgment.	The reliability upon the accuracy and completeness of customer data internal to the bank depends upon the perception of the credit officer, internal auditors and credit control judgment.

2. To what extent can you rely upon the accuracy and completeness of customer data from sources external to your bank?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Bank account. Govt. Semi.Govt/ MNCs.	Perception	Hype the salary. Up to 60 % accuracy.	Since there is no private credit bureau, we normally ask for certified statements to be presented by the customer.	Cross verification Document Backup.	Cross verification. Certified statements.

3. To what extent does the verification of the data on the customer application forms affect the credit decision process? What do you do for the missing information?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Information regarding credit to substantiate documents. Hard copy of loan application is critical. Missing information is to be filled.	No credit decision without customer verification and with missing information.	Paper Based	Normally, the revenue is inflated and living suppressed. Underwriting is typically conservative, not exactly "risk averse" but "risk aware"	Constant back-up	No credit decision without customer verification and with missing information. Underwriting typically conservative, not exactly "risk averse" but "risk aware". Means without proper verification of the data on the customer application forms the credit is not granted.

4. Are there any specific (not provided) application responses that are significant in affecting the decision process within your bank?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Regular revision of application forms.	Loan application form to be changed every one year according the growing needs of the market.	Yes the end use of the loan and the source of income.	Our main focus is on quality of loan than quantity. Hence, we believe in focussing to gather as much information before the credit is granted.	If there is no information in the application form, then relationship officer would pursue with the applicant to get those information.	The end use of the loan and the focus on the quality of loan are significant in affecting the credit decision process.

5. What steps, if any, does your bank take to evaluate the accuracy and honesty of the information provided by customers on their application for credit?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Audited statement to be submitted. Believe in the customer.	Cross verification.	Cross Verification	We believe in cross verification of the information provided.	Back up documents and references.	Through cross verification the bank would evaluate the accuracy and honesty of the information provided by the customers.

6. Does your bank make use of the credit information bureau report? Or credit reference or inter-bank reference? If relevant, how reliable do you consider it to be? Does this report/reference play an important part in the credit decision process?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Gap. Difficult. Competition.	100% CIB. Interbank reference is easy to obtain and authentic.	CIB and Interbank reference. In nascent stage, data is incomplete, so credit reference of the individual is taken.	CIB report and interbank reference.	CIB report (updated three monthly). Interbank reference is usually lacking in information.	The banks would use CIB report and interbank reference.

Section C: Model Development

1.Can you describe how your bank has used or intends to use historic data in the development of credit scoring models? Will this involve data from accepted customers, rejected applications, and/or accepted customers only with known outcomes?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes. File back up for rejection with reasons and do a follow up on rejected applications.	Yes	5 years. Database maintained in excel sheet. Performance history.	Databases maintain not much.	Yes. Judgmental	The banks intend to use historic data for model development.

2. Is the process of augmentation (reject inference) important while developing the model? How do you incorporate this in your model development?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes	Yes, information.	Yes, reject reason has to be defined.	Very important, because it would enable us to study why the loan was rejected and what would be the outcome if it was accepted.	Not now, but in future this has to be incorporated.	Reject inference is an important criterion while developing the model.

3. What range of variables/factors do you anticipate any formal model will consider, and in turn, include?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Salary, cash flow. But not possible for portfolio.	Monthly salary	Salary (monthly), age, profession, income range vis a vis living expenses, family size, years of employment, demographic and geographic variables.	The variables would depend on the applicant's willingness and ability to pay. The main variable would naturally be his salary or source of income.	Justification of needs. Why the loan is required and how much. Authentication Operating Cash flow. Collateral.	Salary and the applicant's willingness and ability to pay.

4. What internal and external variables/factors would you most likely consider as potential predictors of loan success/default?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Willingness and the attitude to pay.	Salary, employment consistency, age, gender, personal references, collateral.	Salary, profession, willingness and ability to pay. Education and three years in job.	Employment consistency, age, gender monthly income applies.	Monthly income, family structure, repayment history. Political decision and the tax.	Salary, Employment, Age, Collateral.

5. Are there any potential problems relating to scoring errors?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
There might be certain factor which might affect losing genuine customer.	The experience of the credit officer might be lost if we use credit scoring.	Yes, numbers or scored based on documents/ information which may not be accurate. In judgmental other factors play cannot capture all in scores.	There might be other factors like economic conditions, inflation which credit scoring might not consider wherein judgmental system can come into play.	Scoring is fixed. Limited variables. Case to case basis.	Scoring errors might lose genuine customer. The experience of the credit officer is lost if credit scoring is used. Economic conditions, inflations should be incorporated in the model.

6. If there were any overrides in the credit decision process, would the overrides data be analysed and built back into the model? If so, how

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Local considerations.	There are overrides, after it is regular.	Based on the no. of overrides of a particular type/performance.	There are overrides. However, we have to look at the degree of overrides in analysing it and putting back into the model.	May be doing on the back-up. Learning from experience.	Overrides are there with considerations to local branch level issues.

Section D: Implementation Issues

1. With whom will responsibility lay for the operational implementation of credit decision models in the front line of your business?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Sales Department	Head Office.	Driven by business/credit. Input by business and approved by credit.	With the credit risk assessment department.	Credit control department. The relationship officer and the risk assessment department should coordinate with the credit control department.	The responsibility for the operational implementation of credit decision model lay with the credit risk assessment/credit control department.

2. What are the technical issues associated with the implementation of a quantitative credit decision models?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Software	Infrastructure development.	Management of infrastructure and historical data.	In our bank, the management is very positive about credit risk modelling and our emphasis is on bank soundness and stability.	Training and Management willingness. Automation.	Technical issues related to the infrastructure development, software, training.

3. What are the business issues associated with the implementation of a quantitative credit decision models?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
If reject is less— winner in service delivery.	Senior Management will to adopt the models.	Positive impact.	Credit risk modelling is about managing it and not eliminating it. If we are able to properly manage it and bring the NPL down then it would send a positive signal in the market.	Management and Security.	The implementation of the quantitative credit decision models would have a positive impact in the market. Credit risk modelling is about managing it and not eliminating it.

4. What are the cultural issues associated with the implementation of a quantitative credit decision models?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes there might be because of the lack of credit act.	No answer	No consumer credit act. Age factor/ gender. Net worth of the consumer unable to calculate because of lack of credit history.	Till now, the central bank has not issued any guidelines on credit granting policies. There is no act like the consumer credit act (UK) and the ECOA (US). Thus cultural issues creates a problem in model development.	Planning. Because all documents are paper based.	The cultural issues would relate to the lack of credit act, which might be problematic in model development.

5. To what extent, if any, can those implementing the model override the model's decisions? Who triggers this override process?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Internal overrides	Staff references overrides.	Exceeding credit targets. Cap on	Relationship Manager and Risk Manager are separate, so no	Pressure from customer.	There might be internal overrides

		overrides (5%)	overrides. However, there might be overrides from the staff references which is negligible.		through staff references and customer pressure.

6. What levels of overrides do you anticipate taking place in terms of percentage of decisions? Do overrides go in both directions?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Both	Yes on both directions. Sometimes to fulfil the credit targets, we as a credit dept. has to overlook overrides.	Yes there are overrides.	Negligible.	No overrides.	The banks accepted that the credit decisions are not free from overrides.

Section E: Model Evaluation and Performance

1. Is your bank likely to adopt a combination of judgmental/quantitative approaches to credit scoring?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Both	Combination	Both, because of the market requirement.	Has to be a combination.	Yes, a combination.	Combination because of the market requirement.

2. If you choose to rely exclusively on your credit scoring models, will you undertake the assessment of any qualitative risk (sample customers perhaps)?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes	Assessment through the experience of the credit officer will always play a vital role even if we adopt a credit scoring models.	Yes to cross validate the loan decision.	This is needed to cross validate the decision and also for pricing loans.	Yes, we have too. We will do within 5 years.	Yes, to cross validate.

3. How often do you anticipate the validation of your credit scoring models?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Validation	Not sure.	At least once in 2 yrs.	There has to be regular update on the data used in the model. Might be three yrs review.	Management would incorporate users views.	Regular update on the data used in model. Ranged between 2-3 years.

4. What performance criteria will you use to determine this?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Repayment	Target given by HO and the review of targets.	EMI date-current. Delinquency and default, overrides and socio-economic changes.	Management Information System. Likely indicator of 30, 60 and 90 days. And the likely indicator.	Relevance with regulatory requirement. Basel II requirement.	Repayment. Target given by the head office and review of targets. EMI date- current. Delinquency and default (likely indicator of 30, 60 and 90 days). Relevance with regulatory requirement and Basel II requirement.

5. To what extent will the customers be aware of the performance criteria? For example, will mechanisms be put in place for them to provide feedback?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Educated	Customer are aware. Exercise in placed.	Not so sure, but the customer are aware of the performance criteria.	Unstructured.	To some extent.	Through proper customer education. Customers are aware of the performance criteria.

6. Does behavioural scoring help to reset the credit performance criteria in mortgage lending? If yes, how would you incorporate the changes?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes	Past record. Collateral	Going to introduce. Performance marks.	Mortgage lending which we call home loan is driven by the EMI payment. If there is a delinquency in payment behaviour the missed payment could be incorporated, but that is a long way to go. First let us have the basic credit scoring model.	Yes. Other Banks records for behavioural scoring.	Yes. Through performance marks. First let us have the basic credit scoring model.

7. How long do you expect a scoring system to remain operational within your bank before updates take place and what performance criteria do you use or expect to use to indicate its time for replacement?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
No Answer	Yes	No answer	No idea as of now. Once we adopt any model we would see then.	As and when required.	No definite answer. Once they adopt the model they would see.

8. What would you anticipate the size and complexity of any credit scoring model to be in terms of number of factors measured and scored?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
No Answer	Risk department Maintaining data.	No answer.	3 years	User friendly. Complex in nature but not complex to user.	No definite answer.

9. How would you monitor over time the current level of customer evaluation by your bank, in terms of good decisions made for accepted loans?

Bank A	Bank B	Bank C	Bank D	Bank E	Major themes
Yes system is in placed.	Repayment	No. July 2007 (SCB group Basel II)	Management Information System. Portfolio basis by seeing the delinquency level.	No hi-fi stuff. Informed education through judgmental.	Through repayment. Through adoption of Basel II. Portfolio basis by seeing the delinquency level.

Appendix D: Credit Application Forms

D1- Correlation Coefficients
D2 - Collinearity Diagnostics
D3- Omnibus Test of Model Coefficients
D4- Hosmer and Lemeshow Test
D5- Model Summary
D6- SPSS Outputs of Logistic Regression Analysis

D1- Correlation Coefficients

Model		Collinearity Statistics	
		Tolerance	VIF
1	Age of the Applicant	.819	1.220
	Type of Employment	.619	1.615
	Type of Occupation	.619	1.615
	Office Telephone	.701	1.426
	Home Telephone	.846	1.182
	Number of Dependents	.751	1.332
	Purpose of the Loan	.570	1.754
	Loan Amount Requested	.215	4.659
	Other Sources of Finance	.305	3.278
	Stage of the Project	.551	1.816
	Total Assets of the Applicant	.617	1.621
	Total Liabilities of the Applicant	.778	1.286
	Monthly Income (Self)	.003	398.791
	Monthly Income (Spouse)	.036	27.407
	Total Monthly Income (Self and Spouse)	.003	392.344
	Applicant Equity (%)	.308	3.243
	Rate of Interest Charged	.822	1.216
	Loan Duration (yrs)	.721	1.387
	Property Value	.351	2.845

a. Dependent Variable: Quality of the Loan

D3- Omnibus Tests of Model Coefficients:

Step 14	Chi-square	df	Sig.
Step	-1.827	1	0.176
Block	19.606	6	0.003
Model	19.606	6	0.003

D4- Hosmer and Lemeshow Test

	Chi-Square	df	Sig.
Step 14	9.844	8	0.276

D5- Model Summary

	-2 log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 14	166.650	0.092	0.154

Logistic Regression

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[DataSet1] U:\DBA\Thesis\Thesis Documents and Data\Thesis Data\Home_Loan_F
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Case Processing Summary

Unweighted Cases [a]		N	Percent
Selected Cases	Included in Analysis	202	100.0
	Missing Cases	0	.0
	Total	202	100.0
	Unselected Cases	0	.0
	Total	202	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Default/Bad Credit	0
No Default/Good Credit	1

Block 0: Beginning Block

Iteration History[a,b,c]

Iteration		-2 Log likelihood	Coefficients Constant
Step 0	1	188.255	1.307
	2	186.266	1.544
	3	186.256	1.563
	4	186.256	1.563

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 186.256

c. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a,b]

Observed			Predicted: Quality of the Loan: Default/Bad Credit	Predicted: Quality of the Loan: No Default/Good Credit
Step 0	Quality of the Loan	Default/Bad Credit	0	35
		No Default/Good Credit	0	167
		Overall Percentage		

a. Constant is included in the model.

b. The cut value is .500

Classification Table[a,b]

Observed			Predicted: Quality of the Loan: Percentage Correct
Step 0	Quality of the Loan	Default/Bad Credit	.0
		No Default/Good Credit	100.0
		Overall Percentage	82.7

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	1.563	.186	70.657	1	.000	4.771

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	X1	.168	1	.682
		X2	2.226	1	.136
		X3	1.785	1	.182
		X4	2.473	1	.116
		X5	.524	1	.469
		X6	.051	1	.821
		X7	1.180	1	.277
		X8	.238	1	.625
		X9	.148	1	.701

a. Residual Chi-Squares are not computed because of redundancies.

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	X10	2.934	1	.087
		X11	.412	1	.521
		X12	.010	1	.921
		X13	.334	1	.564
		X14	2.660	1	.103
		X15	.900	1	.343
		X16	1.881	1	.170
		X17	.742	1	.389
		X18	.005	1	.945
		X19	.943	1	.332
		X20	.903	1	.342

a. Residual Chi-Squares are not computed because of redundancies.

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Iteration History[a,b,c,d,e,f]

Iteration		-2 Log likelihood	Coefficients				
			Constant	X1	X2	X3	X4
Step 1	1	170.325	2.448	.080	.355	-.075	-.274
	2	161.694	3.638	.115	.763	-.152	-.520
	3	160.704	4.220	.118	1.036	-.199	-.656
	4	160.658	4.309	.118	1.082	-.207	-.683
	5	160.651	4.310	.119	1.083	-.207	-.684
	6	160.648	4.310	.119	1.083	-.207	-.684
Step 2	1	170.330	2.492	.079	.357	-.075	-.277
	2	161.693	3.628	.115	.764	-.152	-.519
	3	160.728	4.134	.120	1.022	-.197	-.647
	4	160.684	4.203	.120	1.062	-.203	-.672
	5	160.677	4.203	.121	1.063	-.204	-.673

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients						
		X5	X6	X7	X8	X9	X11	X12
Step 1	1	.059	.032	-.452	.000	.000	.181	.000
	2	-.013	.064	-.697	.000	.000	.283	.000
	3	-.119	.078	-.775	.000	.000	.312	.000
	4	-.141	.080	-.781	.000	.000	.313	.000
	5	-.141	.080	-.781	.000	.000	.313	.000
	6	-.141	.080	-.781	.000	.000	.313	.000
Step 2	1		.032	-.453	.000	.000	.179	.000
	2		.064	-.697	.000	.000	.283	.000
	3		.079	-.775	.000	.000	.318	.000
	4		.082	-.781	.000	.000	.320	.000
	5		.082	-.781	.000	.000	.320	.000

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients					
		X13	X14	X15	X16	X17	X18
Step 1	1	.000	.000	.000	.000	.005	-.130
	2	.000	.000	.000	.000	.006	-.225
	3	.000	.000	.000	.000	.008	-.277
	4	.000	.000	.000	.000	.008	-.286
	5	.000	.000	.000	.000	.008	-.286
	6	.000	.000	.000	.000	.008	-.286
Step 2	1	.000	.000	.000	.000	.005	-.129
	2	.000	.000	.000	.000	.006	-.225
	3	.000	.000	.000	.000	.007	-.277
	4	.000	.000	.000	.000	.008	-.286
	5	.000	.000	.000	.000	.008	-.286

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients	
		X19	X20
Step 1	1	.132	.000
	2	.219	.000
	3	.251	.000
	4	.251	.000
	5	.251	.000
	6	.251	.000
Step 2	1	.136	.000
	2	.218	.000
	3	.240	.000
	4	.237	.000
	5	.237	.000

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		-2 Log likelihood	Coefficients				
			Constant	X1	X2	X3	X4
Step 3	1	170.369	2.485	.081	.360	-.075	-.272
	2	161.701	3.620	.117	.767	-.152	-.515
	3	160.749	4.129	.121	1.024	-.197	-.645
	4	160.718	4.196	.122	1.064	-.203	-.669
	5	160.718	4.196	.123	1.065	-.204	-.670
	6	160.718	4.196	.123	1.065	-.204	-.670
Step 4	1	170.491	2.752	.076	.378	-.079	-.273
	2	161.822	4.023	.108	.792	-.159	-.528
	3	160.894	4.612	.109	1.055	-.205	-.668
	4	160.869	4.718	.108	1.099	-.212	-.694
	5	160.869	4.721	.108	1.100	-.213	-.695
	6	160.869	4.721	.108	1.100	-.213	-.695
Step 5	1	170.621	2.707	.078	.387	-.081	-.254
	2	161.971	3.928	.115	.816	-.162	-.495
	3	161.033	4.496	.118	1.092	-.209	-.630
	4	161.008	4.601	.118	1.137	-.217	-.657
	5	161.008	4.605	.118	1.138	-.217	-.658
	6	161.008	4.605	.118	1.138	-.217	-.658
Step 6	1	170.690	2.748	.087	.389	-.079	-.269
	2	162.115	4.036	.134	.821	-.158	-.532
	3	161.186	4.622	.139	1.103	-.206	-.676
	4	161.161	4.725	.139	1.149	-.214	-.703
	5	161.161	4.728	.139	1.150	-.214	-.704
	6	161.161	4.728	.139	1.150	-.214	-.704
Step 7	1	171.110	3.019		.387	-.081	-.283
	2	162.562	4.353		.838	-.168	-.561
	3	161.609	4.907		1.135	-.220	-.715
	4	161.585	5.006		1.183	-.228	-.745
	5	161.585	5.009		1.184	-.228	-.746
	6	161.585	5.010		1.184	-.228	-.746
Step 8	1	171.249	3.003		.386	-.084	-.277
	2	162.888	4.251		.837	-.176	-.544

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients						
		X5	X6	X7	X8	X9	X11	X12
Step 3	1		.031	-.450	.000	.000	.180	.000
	2		.065	-.696	.000	.000	.283	.000
	3		.080	-.774	.000	.000	.318	.000
	4		.083	-.780	.000	.000	.320	.000
	5		.083	-.779	.000	.000	.320	.000
	6		.083	-.779	.000	.000	.320	.000
Step 4	1		.022	-.466	.000	.000	.183	.000
	2		.049	-.719	.000	.000	.286	.000
	3		.060	-.803	.000	.000	.322	.000
	4		.061	-.811	.000	.000	.326	.000
	5		.061	-.812	.000	.000	.326	.000
	6		.061	-.812	.000	.000	.326	.000
Step 5	1		.022	-.465	.000	.000	.186	.000
	2		.050	-.722	.000	.000	.295	.000
	3		.062	-.808	.000	.000	.334	.000
	4		.063	-.818	.000	.000	.338	.000
	5		.063	-.818	.000	.000	.338	.000
	6		.063	-.818	.000	.000	.338	.000
Step 6	1			-.461	.000	.000	.183	.000
	2			-.712	.000	.000	.289	.000
	3			-.797	.000	.000	.327	.000
	4			-.806	.000	.000	.330	.000
	5			-.806	.000	.000	.330	.000
	6			-.806	.000	.000	.330	.000
Step 7	1			-.455	.000	.000	.173	.000
	2			-.699	.000	.000	.271	.000
	3			-.784	.000	.000	.308	.000
	4			-.794	.000	.000	.313	.000
	5			-.794	.000	.000	.312	.000
	6			-.794	.000	.000	.312	.000
Step 8	1			-.460	.000	.000	.178	.000
	2			-.712	.000	.000	.284	.000

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than . 001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than . 001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients					
		X13	X14	X15	X16	X17	X18
Step 3	1	.000	.000		.000	.005	-.132
	2	.000	.000		.000	.007	-.228
	3	.000	.000		.000	.008	-.279
	4	.000	.000		.000	.008	-.289
	5	.000	.000		.000	.008	-.289
	6	.000	.000		.000	.008	-.289
Step 4	1	.000	.000		.000		-.126
	2	.000	.000		.000		-.220
	3	.000	.000		.000		-.271
	4	.000	.000		.000		-.280
	5	.000	.000		.000		-.280
	6	.000	.000		.000		-.280
Step 5	1		.000		.000		-.123
	2		.000		.000		-.217
	3		.000		.000		-.268
	4		.000		.000		-.277
	5		.000		.000		-.277
	6		.000		.000		-.277
Step 6	1		.000		.000		-.123
	2		.000		.000		-.218
	3		.000		.000		-.267
	4		.000		.000		-.275
	5		.000		.000		-.276
	6		.000		.000		-.276
Step 7	1		.000		.000		-.121
	2		.000		.000		-.204
	3		.000		.000		-.247
	4		.000		.000		-.254
	5		.000		.000		-.255
	6		.000		.000		-.255
Step 8	1		.000				-.113
	2		.000				-.180

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients X19	X20
Step 3	1	.132	.000
	2	.216	.000
	3	.237	.000
	4	.234	.000
	5	.233	.000
	6	.233	.000
Step 4	1	.116	.000
	2	.197	.000
	3	.219	.000
	4	.217	.000
	5	.216	.000
	6	.216	.000
Step 5	1	.112	.000
	2	.193	.000
	3	.216	.000
	4	.214	.000
	5	.214	.000
	6	.214	.000
Step 6	1	.112	.000
	2	.191	.000
	3	.213	.000
	4	.211	.000
	5	.211	.000
	6	.211	.000
Step 7	1	.098	.000
	2	.176	.000
	3	.199	.000
	4	.197	.000
	5	.196	.000
	6	.196	.000
Step 8	1	.087	.000
	2	.153	.000

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		-2 Log likelihood	Coefficients				
			Constant	X1	X2	X3	X4
Step 8	3	161.962	4.694		1.148	-.233	-.695
	4	161.939	4.765		1.201	-.242	-.725
	5	161.939	4.768		1.202	-.242	-.726
	6	161.939	4.768		1.202	-.242	-.726
Step 9	1	171.510	2.927		.390	-.088	-.268
	2	163.251	4.112		.839	-.183	-.528
	3	162.307	4.535		1.143	-.240	-.677
	4	162.278	4.617		1.196	-.250	-.709
	5	162.278	4.620		1.197	-.250	-.710
	6	162.278	4.620		1.197	-.250	-.710
Step 10	1	171.668	2.152		.380	-.089	-.265
	2	163.445	2.940		.825	-.185	-.524
	3	162.524	3.159		1.123	-.242	-.674
	4	162.499	3.185		1.173	-.251	-.705
	5	162.499	3.185		1.174	-.252	-.706
	6	162.499	3.185		1.174	-.252	-.706
Step 11	1	172.386	2.145		.374	-.091	-.254
	2	164.291	2.913		.823	-.188	-.505
	3	163.361	3.118		1.131	-.247	-.651
	4	163.336	3.144		1.182	-.256	-.682
	5	163.336	3.145		1.183	-.256	-.683
	6	163.336	3.145		1.183	-.256	-.683
Step 12	1	172.694	2.102		.383	-.088	-.249
	2	164.797	2.781		.866	-.182	-.484
	3	163.922	2.933		1.205	-.241	-.617
	4	163.904	2.949		1.260	-.249	-.643
	5	163.904	2.950		1.261	-.249	-.644
	6	163.904	2.950		1.261	-.249	-.644
Step 13	1	173.180	1.818		.471	-.091	
	2	165.614	2.248		1.013	-.190	
	3	164.836	2.273		1.364	-.251	
	4	164.823	2.267		1.417	-.259	

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients						
		X5	X6	X7	X8	X9	X11	X12
Step 8	3			-.800	.000	.000	.329	.000
	4			-.810	.000	.000	.335	.000
	5			-.810	.000	.000	.335	.000
	6			-.810	.000	.000	.335	.000
Step 9	1			-.461	.000	.000	.175	.000
	2			-.709	.000	.000	.275	.000
	3			-.792	.000	.000	.315	.000
	4			-.801	.000	.000	.320	.000
	5			-.801	.000	.000	.320	.000
	6			-.801	.000	.000	.320	.000
Step 10	1			-.452	.000	.000	.175	.000
	2			-.701	.000	.000	.277	.000
	3			-.784	.000	.000	.318	.000
	4			-.794	.000	.000	.323	.000
	5			-.794	.000	.000	.323	.000
	6			-.794	.000	.000	.323	.000
Step 11	1			-.449	.000	.000	.175	
	2			-.699	.000	.000	.280	
	3			-.782	.000	.000	.322	
	4			-.791	.000	.000	.327	
	5			-.791	.000	.000	.327	
	6			-.791	.000	.000	.327	
Step 12	1			-.469	.000	.000	.188	
	2			-.732	.000	.000	.307	
	3			-.823	.000	.000	.358	
	4			-.834	.000	.000	.365	
	5			-.834	.000	.000	.365	
	6			-.834	.000	.000	.365	
Step 13	1			-.465	.000	.000	.185	
	2			-.728	.000	.000	.306	
	3			-.820	.000	.000	.361	
	4			-.832	.000	.000	.369	

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients					
		X13	X14	X15	X16	X17	X18
Step 8	3		.000				-.210
	4		.000				-.215
	5		.000				-.215
	6		.000				-.215
Step 9	1		.000				-.082
	2		.000				-.125
	3		.000				-.147
	4		.000				-.153
	5		.000				-.154
	6		.000				-.154
Step 10	1		.000				
	2		.000				
	3		.000				
	4		.000				
	5		.000				
	6		.000				
Step 11	1		.000				
	2		.000				
	3		.000				
	4		.000				
	5		.000				
	6		.000				
Step 12	1		.000				
	2		.000				
	3		.000				
	4		.000				
	5		.000				
	6		.000				
Step 13	1		.000				
	2		.000				
	3		.000				
	4		.000				

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients	
		X19	X20
Step 8	3	.173	.000
	4	.171	.000
	5	.171	.000
	6	.171	.000
Step 9	1		.000
	2		.000
	3		.000
	4		.000
	5		.000
	6		.000
Step 10	1		.000
	2		.000
	3		.000
	4		.000
	5		.000
	6		.000
Step 11	1		.000
	2		.000
	3		.000
	4		.000
	5		.000
	6		.000
Step 12	1		
	2		
	3		
	4		
	5		
	6		
Step 13	1		
	2		
	3		
	4		

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		-2 Log likelihood	Coefficients				
			Constant	X1	X2	X3	X4
Step 13	5	164.823	2.267		1.418	-.259	
Step 14	1	174.864	1.879		.483	-.116	
	2	167.470	2.332		1.067	-.233	
	3	166.663	2.367		1.450	-.302	
	4	166.650	2.365		1.505	-.311	
	5	166.650	2.365		1.505	-.311	

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients						
		X5	X6	X7	X8	X9	X11	X12
Step 13	5			-.832	.000	.000	.369	
Step 14	1			-.477	.000	.000	.197	
	2			-.734	.000	.000	.315	
	3			-.823	.000	.000	.366	
	4			-.835	.000	.000	.374	
	5			-.835	.000	.000	.374	

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients					
		X13	X14	X15	X16	X17	X18
Step 13	5		.000				
Step 14	1						
	2						
	3						
	4						
	5						

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than . 001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than . 001.

Iteration History[a,b,c,d,e,f]

Iteration		Coefficients	
		X19	X20
Step 13	5		
Step 14	1		
	2		
	3		
	4		
	5		

a. Method: Backward Stepwise (Likelihood Ratio)

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 186.256

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than . 001.

e. Redundancies in Design Matrix:
X10 = X8 - X9

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than . 001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	25.608	19	.142
	Block	25.608	19	.142

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Model	25.608	19	.142
Step 2[a]	Step	-.029	1	.866
	Block	25.579	18	.110
	Model	25.579	18	.110
Step 3[a]	Step	-.041	1	.839
	Block	25.538	17	.083
	Model	25.538	17	.083
Step 4[a]	Step	-.151	1	.697
	Block	25.387	16	.063
	Model	25.387	16	.063
Step 5[a]	Step	-.139	1	.710
	Block	25.248	15	.047
	Model	25.248	15	.047
Step 6[a]	Step	-.153	1	.695
	Block	25.095	14	.034
	Model	25.095	14	.034
Step 7[a]	Step	-.423	1	.515
	Block	24.671	13	.025
	Model	24.671	13	.025
Step 8[a]	Step	-.354	1	.552
	Block	24.317	12	.018
	Model	24.317	12	.018
Step 9[a]	Step	-.339	1	.560
	Block	23.978	11	.013
	Model	23.978	11	.013
Step 10[a]	Step	-.221	1	.639
	Block	23.757	10	.008
	Model	23.757	10	.008
Step 11[a]	Step	-.837	1	.360
	Block	22.920	9	.006
	Model	22.920	9	.006
Step 12[a]	Step	-.568	1	.451
	Block	22.351	8	.004
	Model	22.351	8	.004
Step 13[a]	Step	-.918	1	.338
	Block	21.433	7	.003
	Model	21.433	7	.003
Step 14[a]	Step	-1.827	1	.176
	Block	19.606	6	.003
	Model	19.606	6	.003

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	160.648[a]	.119	.198
2	160.677[b]	.119	.197
3	160.718[a]	.119	.197
4	160.869[a]	.118	.196
5	161.008[a]	.117	.195
6	161.161[a]	.117	.194
7	161.585[a]	.115	.191
8	161.939[a]	.113	.188
9	162.278[a]	.112	.186
10	162.499[a]	.111	.184
11	163.336[a]	.107	.178
12	163.904[a]	.105	.174
13	164.823[b]	.101	.167
14	166.650[b]	.092	.154

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	19.292	8	.013
2	13.663	8	.091
3	13.718	8	.089
4	13.933	8	.084
5	14.719	8	.065
6	15.663	8	.047
7	6.994	8	.537
8	12.100	8	.147
9	7.302	8	.504
10	7.771	8	.456
11	6.472	8	.594
12	7.774	8	.456
13	5.520	8	.701
14	9.844	8	.276

Contingency Table for Hosmer and Lemeshow Test

		Quality of the Loan = Default/Bad Credit		Quality of the Loan = No Default/Good Credit		
		Observed	Expected	Observed	Expected	Total
Step 1	1	12	10.271	8	9.729	20
	2	3	5.701	17	14.299	20
	3	5	4.408	15	15.592	20
	4	0	3.794	20	16.206	20
	5	3	2.981	17	17.019	20
	6	7	2.442	13	17.558	20
	7	1	2.114	19	17.886	20
	8	3	1.623	17	18.377	20
	9	1	1.214	19	18.786	20
	10	0	.451	22	21.549	22
Step 2	1	12	10.295	8	9.705	20
	2	3	5.665	17	14.335	20
	3	4	4.420	16	15.580	20
	4	1	3.799	19	16.201	20
	5	4	2.976	16	17.024	20
	6	6	2.441	14	17.559	20
	7	1	2.093	19	17.907	20
	8	3	1.628	17	18.372	20
	9	1	1.230	19	18.770	20
	10	0	.456	22	21.544	22
Step 3	1	12	10.288	8	9.712	20
	2	3	5.678	17	14.322	20
	3	4	4.429	16	15.571	20
	4	1	3.800	19	16.200	20
	5	4	2.974	16	17.026	20
	6	6	2.435	14	17.565	20
	7	1	2.088	19	17.912	20
	8	3	1.627	17	18.373	20
	9	1	1.218	19	18.782	20
	10	0	.463	22	21.537	22
Step 4	1	12	10.227	8	9.773	20
	2	3	5.763	17	14.237	20
	3	3	4.429	17	15.571	20
	4	2	3.740	18	16.260	20
	5	3	2.997	17	17.003	20
	6	7	2.506	13	17.494	20
	7	2	2.071	18	17.929	20
	8	2	1.592	18	18.408	20
	9	1	1.194	19	18.806	20

Contingency Table for Hosmer and Lemeshow Test

		Quality of the Loan = Default/Bad Credit		Quality of the Loan = No Default/Good Credit		
		Observed	Expected	Observed	Expected	Total
Step 4	10	0	.481	22	21.519	22
Step 5	1	12	10.187	8	9.813	20
	2	3	5.783	17	14.217	20
	3	3	4.494	17	15.506	20
	4	2	3.721	18	16.279	20
	5	3	3.011	17	16.989	20
	6	7	2.494	13	17.506	20
	7	2	2.022	18	17.978	20
	8	1	1.595	19	18.405	20
	9	2	1.219	18	18.781	20
	10	0	.475	22	21.525	22
Step 6	1	12	10.140	8	9.860	20
	2	3	5.777	17	14.223	20
	3	4	4.554	16	15.446	20
	4	1	3.636	19	16.364	20
	5	4	3.034	16	16.966	20
	6	7	2.535	13	17.465	20
	7	1	2.079	19	17.921	20
	8	2	1.548	18	18.452	20
	9	1	1.217	19	18.783	20
	10	0	.481	22	21.519	22
Step 7	1	12	9.983	8	10.017	20
	2	3	5.862	17	14.138	20
	3	4	4.574	16	15.426	20
	4	2	3.596	18	16.404	20
	5	3	3.069	17	16.931	20
	6	4	2.565	16	17.435	20
	7	3	2.161	18	18.839	21
	8	3	1.552	17	18.448	20
	9	1	1.185	19	18.815	20
	10	0	.453	21	20.547	21
Step 8	1	12	9.863	8	10.137	20
	2	3	6.008	17	13.992	20
	3	5	4.534	15	15.466	20
	4	1	3.650	19	16.350	20
	5	2	2.951	18	17.049	20
	6	6	2.595	14	17.405	20
	7	3	2.072	17	17.928	20
	8	2	1.609	19	19.391	21

Contingency Table for Hosmer and Lemeshow Test

		Quality of the Loan = Default/Bad Credit		Quality of the Loan = No Default/Good Credit		
		Observed	Expected	Observed	Expected	Total
Step 8	9	1	1.214	19	18.786	20
	10	0	.504	21	20.496	21
Step 9	1	10	9.716	10	10.284	20
	2	5	6.028	15	13.972	20
	3	5	4.633	15	15.367	20
	4	2	3.596	18	16.404	20
	5	2	2.995	18	17.005	20
	6	3	2.547	17	17.453	20
	7	5	2.129	15	17.871	20
	8	1	1.595	19	18.405	20
	9	2	1.222	18	18.778	20
	10	0	.538	22	21.462	22
Step 10	1	11	10.035	10	10.965	21
	2	3	5.910	17	14.090	20
	3	6	4.603	14	15.397	20
	4	2	3.707	19	17.293	21
	5	2	2.958	18	17.042	20
	6	4	2.476	16	17.524	20
	7	4	2.068	16	17.932	20
	8	2	1.604	18	18.396	20
	9	1	1.177	19	18.823	20
	10	0	.462	20	19.538	20
Step 11	1	11	9.468	9	10.532	20
	2	4	6.044	16	13.956	20
	3	3	4.684	17	15.316	20
	4	3	3.646	17	16.354	20
	5	3	3.013	17	16.987	20
	6	4	2.536	16	17.464	20
	7	4	2.157	16	17.843	20
	8	1	1.673	19	18.327	20
	9	2	1.239	18	18.761	20
	10	0	.541	22	21.459	22
Step 12	1	10	9.540	10	10.460	20
	2	4	5.685	16	14.315	20
	3	3	4.655	17	15.345	20
	4	6	3.615	14	16.385	20
	5	2	3.132	19	17.868	21
	6	4	2.720	17	18.280	21
	7	2	2.225	18	17.775	20

Contingency Table for Hosmer and Lemeshow Test

		Quality of the Loan = Default/Bad Credit		Quality of the Loan = No Default/Good Credit		
		Observed	Expected	Observed	Expected	Total
Step 12	8	3	1.677	17	18.323	20
	9	0	1.288	20	18.712	20
	10	1	.464	19	19.536	20
Step 13	1	9	9.618	11	10.382	20
	2	6	5.478	14	14.522	20
	3	3	4.394	17	15.606	20
	4	4	3.698	16	16.302	20
	5	2	3.035	18	16.965	20
	6	3	2.574	17	17.426	20
	7	4	2.366	17	18.634	21
	8	1	1.842	19	18.158	20
	9	3	1.398	17	18.602	20
	10	0	.596	21	20.404	21
Step 14	1	10	9.218	10	10.782	20
	2	4	5.489	16	14.511	20
	3	3	4.309	17	15.691	20
	4	5	3.825	16	17.175	21
	5	3	3.104	17	16.896	20
	6	1	2.720	19	17.280	20
	7	4	2.412	17	18.588	21
	8	1	1.914	19	18.086	20
	9	4	1.465	16	18.535	20
	10	0	.543	20	19.457	20

Classification Table[a]

			Predicted	
			Quality of the Loan	
Observed			Default/Bad Credit	No Default/Good Credit
Step 1	Quality of the Loan	Default/Bad Credit	8	27
		No Default/Good Credit	4	163
		Overall Percentage		
Step 2	Quality of the Loan	Default/Bad Credit	8	27
		No Default/Good Credit	4	163
		Overall Percentage		

a. The cut value is .500

Classification Table[a]

Observed			Predicted: Quality of the Loan — Percentage Correct
Step 1	Quality of the Loan	Default/Bad Credit	22.9
		No Default/Good Credit	97.6
		Overall Percentage	84.7
Step 2	Quality of the Loan	Default/Bad Credit	22.9
		No Default/Good Credit	97.6
		Overall Percentage	84.7

a. The cut value is .500

Classification Table[a]

Observed			Predicted: Quality of the Loan: Default/Bad Credit	Predicted: Quality of the Loan: No Default/Good Credit
Step 3	Quality of the Loan	Default/Bad Credit	8	27
		No Default/Good Credit	4	163
		Overall Percentage		
Step 4	Quality of the Loan	Default/Bad Credit	8	27
		No Default/Good Credit	4	163
		Overall Percentage		
Step 5	Quality of the Loan	Default/Bad Credit	8	27
		No Default/Good Credit	4	163
		Overall Percentage		
Step 6	Quality of the Loan	Default/Bad Credit	7	28
		No Default/Good Credit	2	165
		Overall Percentage		
Step 7	Quality of the Loan	Default/Bad Credit	5	30
		No Default/Good Credit	1	166
		Overall Percentage		
Step 8	Quality of the Loan	Default/Bad Credit	6	29
		No Default/Good Credit	1	166
		Overall Percentage		
Step 9	Quality of the Loan	Default/Bad Credit	5	30
		No Default/Good Credit	0	167
		Overall Percentage		
Step 10	Quality of the Loan	Default/Bad Credit	6	29
		No Default/Good Credit	1	166
		Overall Percentage		
Step 11	Quality of the Loan	Default/Bad Credit	5	30
		No Default/Good Credit	0	167
		Overall Percentage		
Step 12	Quality of the Loan	Default/Bad Credit	6	29
		No Default/Good Credit	2	165
		Overall Percentage		
Step 13	Quality of the Loan	Default/Bad Credit	6	29
		No Default/Good Credit	2	165
		Overall Percentage		
Step 14	Quality of the Loan	Default/Bad Credit	3	32
		No Default/Good Credit	1	166
		Overall Percentage		

a. The cut value is .500

Classification Table[a]

Observed			Predicted: Quality of the Loan – Percentage Correct
Step 3	Quality of the Loan	Default/Bad Credit	22.9
		No Default/Good Credit	97.6
		Overall Percentage	84.7
Step 4	Quality of the Loan	Default/Bad Credit	22.9
		No Default/Good Credit	97.6
		Overall Percentage	84.7
Step 5	Quality of the Loan	Default/Bad Credit	22.9
		No Default/Good Credit	97.6
		Overall Percentage	84.7
Step 6	Quality of the Loan	Default/Bad Credit	20.0
		No Default/Good Credit	98.8
		Overall Percentage	85.1
Step 7	Quality of the Loan	Default/Bad Credit	14.3
		No Default/Good Credit	99.4
		Overall Percentage	84.7
Step 8	Quality of the Loan	Default/Bad Credit	17.1
		No Default/Good Credit	99.4
		Overall Percentage	85.1
Step 9	Quality of the Loan	Default/Bad Credit	14.3
		No Default/Good Credit	100.0
		Overall Percentage	85.1
Step 10	Quality of the Loan	Default/Bad Credit	17.1
		No Default/Good Credit	99.4
		Overall Percentage	85.1
Step 11	Quality of the Loan	Default/Bad Credit	14.3
		No Default/Good Credit	100.0
		Overall Percentage	85.1
Step 12	Quality of the Loan	Default/Bad Credit	17.1
		No Default/Good Credit	98.8
		Overall Percentage	84.7
Step 13	Quality of the Loan	Default/Bad Credit	17.1
		No Default/Good Credit	98.8
		Overall Percentage	84.7
Step 14	Quality of the Loan	Default/Bad Credit	8.6
		No Default/Good Credit	99.4
		Overall Percentage	83.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 1[a]	X1	.119	.226	.276	1	.599
	X2	1.083	.643	2.838	1	.092
	X3	-.207	.127	2.651	1	.103
	X4	-.684	.727	.886	1	.347
	X5	-.141	.879	.026	1	.873
	X6	.080	.173	.215	1	.643
	X7	-.781	.346	5.081	1	.024
	X8	.000	.000	1.638	1	.201
	X9	.000	.000	2.086	1	.149
	X11	.313	.213	2.150	1	.143
	X12	.000	.000	.625	1	.429
	X13	.000	.000	.175	1	.676
	X14	.000	.001	.015	1	.902
	X15	.000	.001	.009	1	.923
	X16	.000	.001	.013	1	.909
	X17	.008	.022	.144	1	.704
	X18	-.286	.351	.664	1	.415
	X19	.251	.316	.631	1	.427
	X20	.000	.000	.972	1	.324
	Constant	4.310	3.645	1.398	1	.237
Step 2[a]	X1	.121	.225	.287	1	.592
	X2	1.063	.628	2.864	1	.091
	X3	-.204	.125	2.659	1	.103
	X4	-.673	.723	.867	1	.352
	X6	.082	.172	.227	1	.634
	X7	-.781	.347	5.069	1	.024
	X8	.000	.000	1.646	1	.200
	X9	.000	.000	2.090	1	.148
	X11	.320	.208	2.376	1	.123
	X12	.000	.000	.609	1	.435
	X13	.000	.000	.164	1	.685
	X14	.000	.000	.024	1	.878
	X15	.000	.000	.012	1	.911
	X16	.000	.000	.019	1	.889
	X17	.008	.022	.135	1	.714
	X18	-.286	.351	.667	1	.414
	X19	.237	.304	.608	1	.436
	X20	.000	.000	.962	1	.327
	Constant	4.203	3.588	1.372	1	.241

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 1[a]	X1	1.126	.724	1.752
	X2	2.953	.838	10.407
	X3	.813	.634	1.043
	X4	.504	.121	2.098
	X5	.869	.155	4.861
	X6	1.083	.772	1.520
	X7	.458	.232	.903
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.367	.900	2.076
	X12	1.000	1.000	1.000
	X13	1.000	1.000	1.000
	X14	1.000	.998	1.001
	X15	1.000	.998	1.001
	X16	1.000	.999	1.002
	X17	1.008	.966	1.053
	X18	.751	.378	1.495
	X19	1.285	.692	2.386
	X20	1.000	1.000	1.000
	Constant	74.443		
Step 2[a]	X1	1.128	.726	1.753
	X2	2.894	.845	9.909
	X3	.816	.639	1.042
	X4	.510	.124	2.104
	X6	1.086	.775	1.521
	X7	.458	.232	.904
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.378	.917	2.070
	X12	1.000	1.000	1.000
	X13	1.000	1.000	1.000
	X14	1.000	.999	1.001
	X15	1.000	.999	1.001
	X16	1.000	.999	1.001
	X17	1.008	.966	1.052
	X18	.751	.378	1.493
	X19	1.267	.699	2.297
	X20	1.000	1.000	1.000
	Constant	66.911		

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 3[a]	X1	.123	.225	.297	1	.586
	X2	1.065	.628	2.876	1	.090
	X3	-.204	.125	2.659	1	.103
	X4	-.670	.723	.860	1	.354
	X6	.083	.172	.233	1	.629
	X7	-.779	.347	5.046	1	.025
	X8	.000	.000	1.707	1	.191
	X9	.000	.000	2.286	1	.131
	X11	.320	.208	2.363	1	.124
	X12	.000	.000	.596	1	.440
	X13	.000	.000	.158	1	.691
	X14	.000	.000	.984	1	.321
	X16	.000	.000	.422	1	.516
	X17	.008	.022	.151	1	.698
	X18	-.289	.351	.680	1	.410
	X19	.233	.303	.592	1	.442
	X20	.000	.000	1.010	1	.315
	Constant	4.196	3.589	1.367	1	.242
Step 4[a]	X1	.108	.221	.240	1	.624
	X2	1.100	.623	3.113	1	.078
	X3	-.213	.123	2.964	1	.085
	X4	-.695	.724	.923	1	.337
	X6	.061	.163	.142	1	.706
	X7	-.812	.337	5.802	1	.016
	X8	.000	.000	2.471	1	.116
	X9	.000	.000	3.813	1	.051
	X11	.326	.207	2.470	1	.116
	X12	.000	.000	.638	1	.424
	X13	.000	.000	.130	1	.719
	X14	.000	.000	.916	1	.338
	X16	.000	.000	.368	1	.544
	X18	-.280	.347	.650	1	.420
	X19	.216	.299	.524	1	.469
	X20	.000	.000	.987	1	.321
	Constant	4.721	3.327	2.013	1	.156
Step 5[a]	X1	.118	.220	.289	1	.591
	X2	1.138	.618	3.387	1	.066
	X3	-.217	.123	3.105	1	.078
	X4	-.658	.715	.847	1	.358

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 3[a]	X1	1.130	.727	1.756
	X2	2.901	.847	9.933
	X3	.816	.639	1.042
	X4	.512	.124	2.110
	X6	1.087	.776	1.523
	X7	.459	.232	.905
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.377	.916	2.071
	X12	1.000	1.000	1.000
	X13	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X16	1.000	1.000	1.000
	X17	1.009	.966	1.053
	X18	.749	.377	1.489
	X19	1.263	.697	2.287
	X20	1.000	1.000	1.000
	Constant	66.421		
Step 4[a]	X1	1.114	.723	1.718
	X2	3.003	.885	10.191
	X3	.809	.635	1.030
	X4	.499	.121	2.060
	X6	1.063	.772	1.464
	X7	.444	.229	.860
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.385	.923	2.079
	X12	1.000	1.000	1.000
	X13	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X16	1.000	1.000	1.000
	X18	.756	.383	1.492
	X19	1.242	.691	2.232
	X20	1.000	1.000	1.000
	Constant	112.330		
Step 5[a]	X1	1.125	.731	1.732
	X2	3.120	.929	10.478
	X3	.805	.632	1.025
	X4	.518	.128	2.103

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 5[a]	X6	.063	.163	.147	1	.701
	X7	-.818	.337	5.897	1	.015
	X8	.000	.000	2.416	1	.120
	X9	.000	.000	3.816	1	.051
	X11	.338	.204	2.737	1	.098
	X12	.000	.000	.670	1	.413
	X14	.000	.000	.948	1	.330
	X16	.000	.000	.413	1	.521
	X18	-.277	.348	.632	1	.426
	X19	.214	.300	.507	1	.476
	X20	.000	.000	1.113	1	.292
	Constant	4.605	3.314	1.931	1	.165
Step 6[a]	X1	.139	.214	.419	1	.517
	X2	1.150	.621	3.432	1	.064
	X3	-.214	.123	3.036	1	.081
	X4	-.704	.710	.985	1	.321
	X7	-.806	.335	5.808	1	.016
	X8	.000	.000	2.468	1	.116
	X9	.000	.000	3.773	1	.052
	X11	.330	.204	2.618	1	.106
	X12	.000	.000	.656	1	.418
	X14	.000	.000	.915	1	.339
	X16	.000	.000	.394	1	.530
	X18	-.276	.349	.623	1	.430
	X19	.211	.300	.493	1	.483
	X20	.000	.000	1.014	1	.314
	Constant	4.728	3.302	2.051	1	.152
Step 7[a]	X2	1.184	.620	3.646	1	.056
	X3	-.228	.122	3.513	1	.061
	X4	-.746	.709	1.106	1	.293
	X7	-.794	.334	5.651	1	.017
	X8	.000	.000	2.201	1	.138
	X9	.000	.000	3.522	1	.061
	X11	.312	.201	2.417	1	.120
	X12	.000	.000	.698	1	.404
	X14	.000	.000	.835	1	.361
	X16	.000	.000	.318	1	.573
	X18	-.255	.347	.540	1	.463
	X19	.196	.300	.430	1	.512

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 5[a]	X6	1.065	.773	1.466
	X7	.441	.228	.854
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.402	.939	2.092
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X16	1.000	1.000	1.000
	X18	.758	.383	1.500
	X19	1.238	.688	2.229
	X20	1.000	1.000	1.000
	Constant	99.937		
Step 6[a]	X1	1.149	.755	1.749
	X2	3.159	.936	10.667
	X3	.807	.634	1.027
	X4	.495	.123	1.987
	X7	.446	.232	.860
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.392	.933	2.077
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X16	1.000	1.000	1.000
	X18	.759	.383	1.505
	X19	1.234	.686	2.223
	X20	1.000	1.000	1.000
	Constant	113.110		
Step 7[a]	X2	3.268	.969	11.020
	X3	.796	.627	1.011
	X4	.474	.118	1.904
	X7	.452	.235	.870
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.367	.922	2.027
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X16	1.000	1.000	1.000
	X18	.775	.393	1.529
	X19	1.217	.677	2.189

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 7[a]	X20	.000	.000	.828	1	.363
	Constant	5.010	3.268	2.350	1	.125
Step 8[a]	X2	1.202	.622	3.735	1	.053
	X3	-.242	.120	4.032	1	.045
	X4	-.726	.710	1.044	1	.307
	X7	-.810	.333	5.916	1	.015
	X8	.000	.000	2.128	1	.145
	X9	.000	.000	3.697	1	.055
	X11	.335	.197	2.908	1	.088
	X12	.000	.000	.695	1	.404
	X14	.000	.000	2.589	1	.108
	X18	-.215	.336	.411	1	.522
	X19	.171	.295	.336	1	.562
	X20	.000	.000	.701	1	.402
	Constant	4.768	3.196	2.225	1	.136
Step 9[a]	X2	1.197	.618	3.745	1	.053
	X3	-.250	.120	4.342	1	.037
	X4	-.710	.712	.996	1	.318
	X7	-.801	.333	5.802	1	.016
	X8	.000	.000	2.219	1	.136
	X9	.000	.000	4.351	1	.037
	X11	.320	.194	2.714	1	.099
	X12	.000	.000	.678	1	.410
	X14	.000	.000	2.752	1	.097
	X18	-.154	.325	.224	1	.636
	X20	.000	.000	.820	1	.365
	Constant	4.620	3.248	2.023	1	.155
Step 10[a]	X2	1.174	.616	3.637	1	.057
	X3	-.252	.119	4.441	1	.035
	X4	-.706	.712	.982	1	.322
	X7	-.794	.333	5.694	1	.017
	X8	.000	.000	2.187	1	.139
	X9	.000	.000	4.388	1	.036
	X11	.323	.194	2.769	1	.096
	X12	.000	.000	.748	1	.387
	X14	.000	.000	2.584	1	.108
	X20	.000	.000	.885	1	.347
	Constant	3.185	1.147	7.716	1	.005
Step 11[a]	X2	1.183	.616	3.691	1	.055

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 7[a]	X20	1.000	1.000	1.000
	Constant	149.831		
Step 8[a]	X2	3.327	.983	11.258
	X3	.785	.620	.994
	X4	.484	.120	1.947
	X7	.445	.231	.854
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.398	.951	2.055
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X18	.806	.417	1.558
	X19	1.186	.666	2.114
	X20	1.000	1.000	1.000
	Constant	117.633		
Step 9[a]	X2	3.310	.985	11.124
	X3	.779	.615	.985
	X4	.491	.122	1.984
	X7	.449	.234	.861
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.378	.941	2.017
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X18	.858	.454	1.620
	X20	1.000	1.000	1.000
	Constant	101.528		
Step 10[a]	X2	3.236	.968	10.816
	X3	.777	.615	.983
	X4	.494	.122	1.995
	X7	.452	.236	.868
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.381	.944	2.021
	X12	1.000	1.000	1.000
	X14	1.000	1.000	1.000
	X20	1.000	1.000	1.000
	Constant	24.179		
Step 11[a]	X2	3.264	.976	10.909

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 11[a]	X3	-.256	.119	4.614	1	.032
	X4	-.683	.709	.928	1	.335
	X7	-.791	.331	5.703	1	.017
	X8	.000	.000	2.031	1	.154
	X9	.000	.000	4.269	1	.039
	X11	.327	.194	2.857	1	.091
	X14	.000	.000	2.211	1	.137
	X20	.000	.000	.571	1	.450
	Constant	3.145	1.138	7.640	1	.006
Step 12[a]	X2	1.261	.616	4.189	1	.041
	X3	-.249	.119	4.407	1	.036
	X4	-.644	.703	.839	1	.360
	X7	-.834	.329	6.432	1	.011
	X8	.000	.000	2.835	1	.092
	X9	.000	.000	4.211	1	.040
	X11	.365	.187	3.806	1	.051
	X14	.000	.000	2.311	1	.128
	Constant	2.950	1.094	7.269	1	.007
Step 13[a]	X2	1.418	.596	5.670	1	.017
	X3	-.259	.118	4.807	1	.028
	X7	-.832	.326	6.536	1	.011
	X8	.000	.000	3.694	1	.055
	X9	.000	.000	4.701	1	.030
	X11	.369	.189	3.802	1	.051
	X14	.000	.000	1.951	1	.163
	Constant	2.267	.810	7.830	1	.005
Step 14[a]	X2	1.5054261	0.5980502	6.3364158	1	0.0118284
	X3	-0.3110066	0.1141474	7.4234661	1	0.0064379
	X7	-0.8348210	0.3237010	6.6511809	1	0.0099090
	X8	-0.0000004	0.0000002	4.7436454	1	0.0294067
	X9	0.0000005	0.0000003	3.9529864	1	0.0467883
	X11	0.3737026	0.1882177	3.9421338	1	0.0470910
	Constant	2.3645648	0.7985188	8.7686390	1	0.0030645

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Variables in the Equation

		Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 11[a]	X3	.774	.612	.978
	X4	.505	.126	2.027
	X7	.453	.237	.868
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.387	.949	2.027
	X14	1.000	1.000	1.000
	X20	1.000	1.000	1.000
	Constant	23.221		
Step 12[a]	X2	3.529	1.055	11.803
	X3	.779	.617	.984
	X4	.525	.132	2.083
	X7	.434	.228	.827
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.441	.998	2.080
	X14	1.000	1.000	1.000
	Constant	19.102		
Step 13[a]	X2	4.130	1.285	13.271
	X3	.772	.612	.973
	X7	.435	.230	.823
	X8	1.000	1.000	1.000
	X9	1.000	1.000	1.000
	X11	1.447	.998	2.098
	X14	1.000	1.000	1.000
	Constant	9.653		
Step 14[a]	X2	4.5060732	1.3955231	14.5498815
	X3	0.7327091	0.5858266	0.9164189
	X7	0.4339521	0.2300949	0.8184207
	X8	0.9999996	0.9999993	1.0000000
	X9	1.0000005	1.0000000	1.0000011
	X11	1.4531049	1.0048143	2.1013971
	Constant	10.6394076		

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20.

Correlation Matrix

		Constant	X1	X2	X3	X4	X5	X6
Step 1	Constant	1.000	-.166	.019	-.079	-.308	-.185	-.212
	X1	-.166	1.000	-.080	.192	.072	.053	-.153
	X2	.019	-.080	1.000	-.597	.200	-.197	-.095
	X3	-.079	.192	-.597	1.000	-.058	.173	.013
	X4	-.308	.072	.200	-.058	1.000	.099	.184
	X5	-.185	.053	-.197	.173	.099	1.000	.069
	X6	-.212	-.153	-.095	.013	.184	.069	1.000
	X7	-.215	-.005	-.166	.200	.005	-.002	-.002
	X8	.250	-.255	.058	-.167	-.181	-.015	-.228
	X9	-.240	.219	-.121	.112	.109	.026	.260
	X11	-.107	.126	.133	-.167	.107	.223	.084
	X12	-.008	-.035	.001	.016	-.040	-.098	-.022
	X13	.065	-.103	-.135	.089	-.129	-.093	.001
	X14	-.007	.009	.005	-.006	.007	.010	.006
	X15	-.004	.012	.003	.000	.006	.006	.008
	X16	.006	-.008	-.004	.004	-.006	-.010	-.006
	X17	-.339	.166	-.114	.159	.080	-.084	.311
	X18	-.777	-.097	-.052	-.137	.028	-.005	-.039
	X19	.088	.052	.039	.104	-.064	-.277	.051
	X20	.017	-.154	.157	.034	.011	.046	-.176
Step 2	Constant	1.000	-.160	-.020	-.049	-.296		-.204
	X1	-.160	1.000	-.071	.185	.065		-.155
	X2	-.020	-.071	1.000	-.581	.227		-.081
	X3	-.049	.185	-.581	1.000	-.077		.004
	X4	-.296	.065	.227	-.077	1.000		.177
	X6	-.204	-.155	-.081	.004	.177		1.000
	X7	-.222	-.005	-.169	.202	.006		-.001
	X8	.254	-.252	.056	-.166	-.181		-.234
	X9	-.242	.216	-.116	.107	.108		.266
	X11	-.067	.115	.185	-.215	.087		.071
	X12	-.026	-.030	-.018	.033	-.029		-.016
	X13	.049	-.098	-.157	.107	-.121		.006
	X14	-.009	.013	.011	-.012	.010		.009
	X15	-.004	.018	.008	-.002	.008		.013
	X16	.007	-.012	-.010	.010	-.008		-.009
	X17	-.366	.168	-.133	.174	.090		.327
	X18	-.791	-.095	-.052	-.138	.029		-.041
	X19	.037	.072	-.019	.163	-.037		.073
	X20	.027	-.159	.168	.026	.006		-.179
Step 3	Constant	1.000	-.159	-.019	-.049	-.296		-.203
	X1	-.159	1.000	-.072	.186	.065		-.157

Correlation Matrix

		X7	X8	X9	X11	X12	X13	X14
Step 1	Constant	-.215	.250	-.240	-.107	-.008	.065	-.007
	X1	-.005	-.255	.219	.126	-.035	-.103	.009
	X2	-.166	.058	-.121	.133	.001	-.135	.005
	X3	.200	-.167	.112	-.167	.016	.089	-.006
	X4	.005	-.181	.109	.107	-.040	-.129	.007
	X5	-.002	-.015	.026	.223	-.098	-.093	.010
	X6	-.002	-.228	.260	.084	-.022	.001	.006
	X7	1.000	-.020	.119	-.580	-.029	.064	.006
	X8	-.020	1.000	-.830	-.045	.023	-.123	-.019
	X9	.119	-.830	1.000	-.066	-.050	.068	.045
	X11	-.580	-.045	-.066	1.000	-.036	-.169	.005
	X12	-.029	.023	-.050	-.036	1.000	-.039	-.019
	X13	.064	-.123	.068	-.169	-.039	1.000	-.009
	X14	.006	-.019	.045	.005	-.019	-.009	1.000
	X15	.007	-.023	.050	.000	-.017	-.010	1.000
	X16	-.005	.019	-.046	-.005	.018	.008	-1.000
	X17	.231	-.766	.757	-.080	-.071	.107	.020
	X18	.056	.107	-.059	.016	.081	-.030	-.003
	X19	-.025	-.088	-.084	.036	.019	.067	-.019
	X20	-.144	-.041	-.327	.228	-.239	.111	-.019
Step 2	Constant	-.222	.254	-.242	-.067	-.026	.049	-.009
	X1	-.005	-.252	.216	.115	-.030	-.098	.013
	X2	-.169	.056	-.116	.185	-.018	-.157	.011
	X3	.202	-.166	.107	-.215	.033	.107	-.012
	X4	.006	-.181	.108	.087	-.029	-.121	.010
	X6	-.001	-.234	.266	.071	-.016	.006	.009
	X7	1.000	-.022	.120	-.595	-.030	.063	.009
	X8	-.022	1.000	-.829	-.041	.021	-.125	-.032
	X9	.120	-.829	1.000	-.074	-.048	.069	.074
	X11	-.595	-.041	-.074	1.000	-.014	-.153	.004
	X12	-.030	.021	-.048	-.014	1.000	-.049	-.030
	X13	.063	-.125	.069	-.153	-.049	1.000	-.014
	X14	.009	-.032	.074	.004	-.030	-.014	1.000
	X15	.012	-.038	.083	-.003	-.027	-.016	.999
	X16	-.009	.030	-.075	-.004	.028	.012	-1.000
	X17	.234	-.770	.762	-.065	-.080	.099	.035
	X18	.058	.105	-.057	.018	.080	-.030	-.006
	X19	-.025	-.096	-.080	.105	-.008	.043	-.028
	X20	-.144	-.038	-.331	.221	-.234	.118	-.033
Step 3	Constant	-.222	.254	-.245	-.066	-.027	.048	-.114
	X1	-.007	-.249	.210	.116	-.027	-.096	-.117

Correlation Matrix

		X15	X16	X17	X18	X19	X20
Step 1	Constant	-.004	.006	-.339	-.777	.088	.017
	X1	.012	-.008	.166	-.097	.052	-.154
	X2	.003	-.004	-.114	-.052	.039	.157
	X3	.000	.004	.159	-.137	.104	.034
	X4	.006	-.006	.080	.028	-.064	.011
	X5	.006	-.010	-.084	-.005	-.277	.046
	X6	.008	-.006	.311	-.039	.051	-.176
	X7	.007	-.005	.231	.056	-.025	-.144
	X8	-.023	.019	-.766	.107	-.088	-.041
	X9	.050	-.046	.757	-.059	-.084	-.327
	X11	.000	-.005	-.080	.016	.036	.228
	X12	-.017	.018	-.071	.081	.019	-.239
	X13	-.010	.008	.107	-.030	.067	.111
	X14	1.000	-1.000	.020	-.003	-.019	-.019
	X15	1.000	-1.000	.024	-.010	-.015	-.026
	X16	-1.000	1.000	-.020	.004	.020	.019
	X17	.024	-.020	1.000	-.082	.146	-.095
	X18	-.010	.004	-.082	1.000	-.325	-.017
	X19	-.015	.020	.146	-.325	1.000	.070
	X20	-.026	.019	-.095	-.017	.070	1.000
Step 2	Constant	-.004	.007	-.366	-.791	.037	.027
	X1	.018	-.012	.168	-.095	.072	-.159
	X2	.008	-.010	-.133	-.052	-.019	.168
	X3	-.002	.010	.174	-.138	.163	.026
	X4	.008	-.008	.090	.029	-.037	.006
	X6	.013	-.009	.327	-.041	.073	-.179
	X7	.012	-.009	.234	.058	-.025	-.144
	X8	-.038	.030	-.770	.105	-.096	-.038
	X9	.083	-.075	.762	-.057	-.080	-.331
	X11	-.003	-.004	-.065	.018	.105	.221
	X12	-.027	.028	-.080	.080	-.008	-.234
	X13	-.016	.012	.099	-.030	.043	.118
	X14	.999	-1.000	.035	-.006	-.028	-.033
	X15	1.000	-.999	.041	-.017	-.023	-.044
	X16	-.999	1.000	-.035	.007	.029	.033
	X17	.041	-.035	1.000	-.079	.129	-.095
	X18	-.017	.007	-.079	1.000	-.339	-.016
	X19	-.023	.029	.129	-.339	1.000	.086
	X20	-.044	.033	-.095	-.016	.086	1.000
Step 3	Constant		.070	-.367	-.793	.037	.026
	X1		.148	.164	-.093	.075	-.153

Correlation Matrix

		Constant	X1	X2	X3	X4	X5	X6
Step 3	X2	-.019	-.072	1.000	-.581	.227		-.082
	X3	-.049	.186	-.581	1.000	-.076		.004
	X4	-.296	.065	.227	-.076	1.000		.175
	X6	-.203	-.157	-.082	.004	.175		1.000
	X7	-.222	-.007	-.170	.201	.003		-.002
	X8	.254	-.249	.059	-.166	-.178		-.233
	X9	-.245	.210	-.124	.107	.101		.264
	X11	-.066	.116	.186	-.214	.089		.071
	X12	-.027	-.027	-.015	.033	-.028		-.011
	X13	.048	-.096	-.157	.107	-.120		.008
	X14	-.114	-.117	.078	-.251	.044		-.103
	X16	.070	.148	-.057	.192	-.007		.093
	X17	-.367	.164	-.137	.174	.087		.326
	X18	-.793	-.093	-.051	-.138	.030		-.040
	X19	.037	.075	-.018	.164	-.034		.075
	X20	.026	-.153	.171	.027	.012		-.176
Step 4	Constant	1.000	-.112	-.075	.013	-.292		-.098
	X1	-.112	1.000	-.051	.164	.055		-.219
	X2	-.075	-.051	1.000	-.573	.239		-.045
	X3	.013	.164	-.573	1.000	-.098		-.057
	X4	-.292	.055	.239	-.098	1.000		.162
	X6	-.098	-.219	-.045	-.057	.162		1.000
	X7	-.151	-.049	-.144	.173	-.018		-.080
	X8	-.047	-.193	-.067	-.048	-.177		.028
	X9	.058	.131	-.042	-.032	.061		.027
	X11	-.097	.127	.180	-.210	.096		.104
	X12	-.054	-.012	-.025	.047	-.022		.010
	X13	.096	-.114	-.149	.092	-.133		-.025
	X14	-.174	-.093	.062	-.236	.061		-.060
	X16	.127	.125	-.038	.173	-.020		.048
	X18	-.881	-.082	-.063	-.126	.042		-.016
	X19	.086	.064	.004	.145	-.047		.026
	X20	-.003	-.142	.165	.038	.014		-.158
Step 5	Constant	1.000	-.098	-.057	.003	-.279		-.096
	X1	-.098	1.000	-.068	.178	.038		-.225
	X2	-.057	-.068	1.000	-.568	.221		-.047
	X3	.003	.178	-.568	1.000	-.084		-.058
	X4	-.279	.038	.221	-.084	1.000		.156
	X6	-.096	-.225	-.047	-.058	.156		1.000
	X7	-.154	-.043	-.143	.175	-.012		-.082
	X8	-.041	-.209	-.077	-.041	-.188		.026

Correlation Matrix

		X7	X8	X9	X11	X12	X13	X14
Step 3	X2	-.170	.059	-.124	.186	-.015	-.157	.078
	X3	.201	-.166	.107	-.214	.033	.107	-.251
	X4	.003	-.178	.101	.089	-.028	-.120	.044
	X6	-.002	-.233	.264	.071	-.011	.008	-.103
	X7	1.000	-.019	.117	-.595	-.027	.065	-.063
	X8	-.019	1.000	-.829	-.040	.012	-.131	.141
	X9	.117	-.829	1.000	-.077	-.030	.082	-.169
	X11	-.595	-.040	-.077	1.000	-.014	-.154	.164
	X12	-.027	.012	-.030	-.014	1.000	-.052	-.069
	X13	.065	-.131	.082	-.154	-.052	1.000	.034
	X14	-.063	.141	-.169	.164	-.069	.034	1.000
	X16	.071	-.163	.137	-.157	.037	-.074	-.972
	X17	.232	-.768	.760	-.066	-.071	.106	-.129
	X18	.060	.099	-.046	.016	.076	-.032	.261
	X19	-.024	-.101	-.073	.106	-.012	.040	-.118
	X20	-.142	-.047	-.322	.224	-.245	.111	.247
Step 4	Constant	-.151	-.047	.058	-.097	-.054	.096	-.174
	X1	-.049	-.193	.131	.127	-.012	-.114	-.093
	X2	-.144	-.067	-.042	.180	-.025	-.149	.062
	X3	.173	-.048	-.032	-.210	.047	.092	-.236
	X4	-.018	-.177	.061	.096	-.022	-.133	.061
	X6	-.080	.028	.027	.104	.010	-.025	-.060
	X7	1.000	.257	-.108	-.596	-.010	.044	-.036
	X8	.257	1.000	-.610	-.134	-.061	-.075	.057
	X9	-.108	-.610	1.000	-.037	.041	.006	-.095
	X11	-.596	-.134	-.037	1.000	-.018	-.151	.156
	X12	-.010	-.061	.041	-.018	1.000	-.053	-.082
	X13	.044	-.075	.006	-.151	-.053	1.000	.047
	X14	-.036	.057	-.095	.156	-.082	.047	1.000
	X16	.043	-.087	.043	-.149	.050	-.089	-.971
	X18	.077	.065	.015	.010	.067	-.025	.254
	X19	-.056	.002	-.251	.115	-.005	.021	-.109
	X20	-.121	-.177	-.374	.213	-.261	.122	.234
Step 5	Constant	-.154	-.041	.057	-.079	-.048		-.174
	X1	-.043	-.209	.138	.106	-.022		-.093
	X2	-.143	-.077	-.042	.162	-.040		.071
	X3	.175	-.041	-.034	-.201	.054		-.248
	X4	-.012	-.188	.061	.075	-.033		.067
	X6	-.082	.026	.023	.103	.010		-.059
	X7	1.000	.263	-.108	-.598	-.006		-.041
	X8	.263	1.000	-.607	-.147	-.054		.061

Correlation Matrix

		X15	X16	X17	X18	X19	X20
Step 3	X2		-.057	-.137	-.051	-.018	.171
	X3		.192	.174	-.138	.164	.027
	X4		-.007	.087	.030	-.034	.012
	X6		.093	.326	-.040	.075	-.176
	X7		.071	.232	.060	-.024	-.142
	X8		-.163	-.768	.099	-.101	-.047
	X9		.137	.760	-.046	-.073	-.322
	X11		-.157	-.066	.016	.106	.224
	X12		.037	-.071	.076	-.012	-.245
	X13		-.074	.106	-.032	.040	.111
	X14		-.972	-.129	.261	-.118	.247
	X16		1.000	.135	-.231	.142	-.250
	X17		.135	1.000	-.074	.134	-.087
	X18		-.231	-.074	1.000	-.344	-.022
	X19		.142	.134	-.344	1.000	.082
	X20		-.250	-.087	-.022	.082	1.000
Step 4	Constant		.127		-.881	.086	-.003
	X1		.125		-.082	.064	-.142
	X2		-.038		-.063	.004	.165
	X3		.173		-.126	.145	.038
	X4		-.020		.042	-.047	.014
	X6		.048		-.016	.026	-.158
	X7		.043		.077	-.056	-.121
	X8		-.087		.065	.002	-.177
	X9		.043		.015	-.251	-.374
	X11		-.149		.010	.115	.213
	X12		.050		.067	-.005	-.261
	X13		-.089		-.025	.021	.122
	X14		-.971		.254	-.109	.234
	X16		1.000		-.223	.130	-.238
	X18		-.223		1.000	-.335	-.029
	X19		.130		-.335	1.000	.079
	X20		-.238		-.029	.079	1.000
Step 5	Constant		.134		-.884	.086	-.016
	X1		.120		-.089	.067	-.133
	X2		-.056		-.071	.011	.192
	X3		.189		-.122	.139	.024
	X4		-.034		.037	-.045	.036
	X6		.048		-.016	.029	-.155
	X7		.048		.076	-.057	-.128
	X8		-.095		.063	.007	-.176

Correlation Matrix

		Constant	X1	X2	X3	X4	X5	X6
Step 5	X9	.057	.138	-.042	-.034	.061		.023
	X11	-.079	.106	.162	-.201	.075		.103
	X12	-.048	-.022	-.040	.054	-.033		.010
	X14	-.174	-.093	.071	-.248	.067		-.059
	X16	.134	.120	-.056	.189	-.034		.048
	X18	-.884	-.089	-.071	-.122	.037		-.016
	X19	.086	.067	.011	.139	-.045		.029
	X20	-.016	-.133	.192	.024	.036		-.155
Step 6	Constant	1.000	-.121	-.065	-.004	-.267		
	X1	-.121	1.000	-.078	.171	.088		
	X2	-.065	-.078	1.000	-.575	.239		
	X3	-.004	.171	-.575	1.000	-.070		
	X4	-.267	.088	.239	-.070	1.000		
	X7	-.161	-.067	-.149	.167	.002		
	X8	-.036	-.205	-.080	-.037	-.206		
	X9	.058	.145	-.038	-.037	.059		
	X11	-.068	.134	.168	-.196	.063		
	X12	-.051	-.018	-.040	.056	-.036		
	X14	-.172	-.102	.069	-.251	.074		
	X16	.130	.126	-.055	.193	-.037		
	X18	-.889	-.099	-.072	-.122	.031		
	X19	.091	.073	.013	.141	-.042		
	X20	-.031	-.176	.188	.011	.067		
Step 7	Constant	1.000		-.072	.011	-.262		
	X2	-.072		1.000	-.574	.245		
	X3	.011		-.574	1.000	-.092		
	X4	-.262		.245	-.092	1.000		
	X7	-.171		-.155	.185	.005		
	X8	-.058		-.090	.001	-.189		
	X9	.070		-.032	-.070	.035		
	X11	-.052		.186	-.223	.058		
	X12	-.052		-.035	.057	-.037		
	X14	-.169		.062	-.243	.089		
	X16	.130		-.049	.180	-.050		
	X18	-.911		-.082	-.102	.041		
	X19	.106		.017	.132	-.045		
	X20	-.049		.179	.047	.091		
Step 8	Constant	1.000		-.067	-.021	-.253		
	X2	-.067		1.000	-.579	.237		
	X3	-.021		-.579	1.000	-.083		
	X4	-.253		.237	-.083	1.000		

Correlation Matrix

		X7	X8	X9	X11	X12	X13	X14
Step 5	X9	-.108	-.607	1.000	-.031	.027		-.090
	X11	-.598	-.147	-.031	1.000	-.033		.166
	X12	-.006	-.054	.027	-.033	1.000		-.082
	X14	-.041	.061	-.090	.166	-.082		1.000
	X16	.048	-.095	.038	-.167	.047		-.972
	X18	.076	.063	.017	.004	.067		.252
	X19	-.057	.007	-.259	.122	-.005		-.112
	X20	-.128	-.176	-.372	.234	-.254		.229
Step 6	Constant	-.161	-.036	.058	-.068	-.051		-.172
	X1	-.067	-.205	.145	.134	-.018		-.102
	X2	-.149	-.080	-.038	.168	-.040		.069
	X3	.167	-.037	-.037	-.196	.056		-.251
	X4	.002	-.206	.059	.063	-.036		.074
	X7	1.000	.269	-.107	-.596	-.006		-.049
	X8	.269	1.000	-.607	-.152	-.056		.061
	X9	-.107	-.607	1.000	-.034	.020		-.083
	X11	-.596	-.152	-.034	1.000	-.032		.176
	X12	-.006	-.056	.020	-.032	1.000		-.079
	X14	-.049	.061	-.083	.176	-.079		1.000
	X16	.057	-.093	.031	-.177	.046		-.973
	X18	.076	.062	.019	.003	.070		.241
	X19	-.053	.009	-.260	.116	-.001		-.109
	X20	-.149	-.175	-.375	.258	-.253		.216
Step 7	Constant	-.171	-.058	.070	-.052	-.052		-.169
	X2	-.155	-.090	-.032	.186	-.035		.062
	X3	.185	.001	-.070	-.223	.057		-.243
	X4	.005	-.189	.035	.058	-.037		.089
	X7	1.000	.262	-.098	-.595	-.009		-.057
	X8	.262	1.000	-.591	-.132	-.063		.042
	X9	-.098	-.591	1.000	-.060	.026		-.055
	X11	-.595	-.132	-.060	1.000	-.027		.185
	X12	-.009	-.063	.026	-.027	1.000		-.067
	X14	-.057	.042	-.055	.185	-.067		1.000
	X16	.067	-.069	.001	-.190	.034		-.973
	X18	.068	.036	.045	.013	.066		.217
	X19	-.048	.025	-.275	.114	.001		-.105
	X20	-.162	-.225	-.363	.291	-.251		.181
Step 8	Constant	-.185	-.051	.051	-.016	-.070		-.173
	X2	-.159	-.100	-.026	.185	-.025		.057
	X3	.179	.012	-.065	-.198	.047		-.304
	X4	.005	-.195	.036	.049	-.033		.177

Correlation Matrix

		X15	X16	X17	X18	X19	X20
Step 5	X9		.038		.017	-.259	-.372
	X11		-.167		.004	.122	.234
	X12		.047		.067	-.005	-.254
	X14		-.972		.252	-.112	.229
	X16		1.000		-.224	.136	-.228
	X18		-.224		1.000	-.335	-.026
	X19		.136		-.335	1.000	.079
	X20		-.228		-.026	.079	1.000
Step 6	Constant		.130		-.889	.091	-.031
	X1		.126		-.099	.073	-.176
	X2		-.055		-.072	.013	.188
	X3		.193		-.122	.141	.011
	X4		-.037		.031	-.042	.067
	X7		.057		.076	-.053	-.149
	X8		-.093		.062	.009	-.175
	X9		.031		.019	-.260	-.375
	X11		-.177		.003	.116	.258
	X12		.046		.070	-.001	-.253
	X14		-.973		.241	-.109	.216
	X16		1.000		-.212	.131	-.217
	X18		-.212		1.000	-.337	-.029
	X19		.131		-.337	1.000	.084
	X20		-.217		-.029	.084	1.000
Step 7	Constant		.130		-.911	.106	-.049
	X2		-.049		-.082	.017	.179
	X3		.180		-.102	.132	.047
	X4		-.050		.041	-.045	.091
	X7		.067		.068	-.048	-.162
	X8		-.069		.036	.025	-.225
	X9		.001		.045	-.275	-.363
	X11		-.190		.013	.114	.291
	X12		.034		.066	.001	-.251
	X14		-.973		.217	-.105	.181
	X16		1.000		-.186	.123	-.179
	X18		-.186		1.000	-.339	-.055
	X19		.123		-.339	1.000	.103
	X20		-.179		-.055	.103	1.000
Step 8	Constant				-.909	.095	.000
	X2				-.091	.022	.173
	X3				-.063	.106	.084
	X4				.025	-.039	.080

Correlation Matrix

		Constant	X1	X2	X3	X4	X5	X6
Step 8	X7	-.185		-.159	.179	.005		
	X8	-.051		-.100	.012	-.195		
	X9	.051		-.026	-.065	.036		
	X11	-.016		.185	-.198	.049		
	X12	-.070		-.025	.047	-.033		
	X14	-.173		.057	-.304	.177		
	X18	-.909		-.091	-.063	.025		
	X19	.095		.022	.106	-.039		
	X20	.000		.173	.084	.080		
Step 9	Constant	1.000		-.067	-.040	-.249		
	X2	-.067		1.000	-.581	.240		
	X3	-.040		-.581	1.000	-.074		
	X4	-.249		.240	-.074	1.000		
	X7	-.167		-.160	.184	-.011		
	X8	-.055		-.100	.008	-.193		
	X9	.084		-.009	-.056	.015		
	X11	-.036		.184	-.209	.061		
	X12	-.071		-.026	.043	-.032		
	X14	-.175		.054	-.309	.184		
	X18	-.936		-.088	-.022	.016		
	X20	-.019		.160	.089	.088		
Step 10	Constant	1.000		-.428	-.175	-.670		
	X2	-.428		1.000	-.584	.247		
	X3	-.175		-.584	1.000	-.069		
	X4	-.670		.247	-.069	1.000		
	X7	-.308		-.159	.185	-.008		
	X8	-.039		-.105	.013	-.196		
	X9	.139		-.013	-.059	.018		
	X11	-.057		.191	-.207	.058		
	X12	.038		-.022	.048	-.033		
	X14	-.037		.075	-.310	.179		
	X20	-.246		.159	.087	.091		
Step 11	Constant	1.000		-.422	-.178	-.670		
	X2	-.422		1.000	-.589	.241		
	X3	-.178		-.589	1.000	-.062		
	X4	-.670		.241	-.062	1.000		
	X7	-.310		-.159	.185	-.005		
	X8	-.037		-.104	.013	-.202		
	X9	.128		-.012	-.059	.026		
	X11	-.048		.183	-.207	.048		
	X14	-.024		.074	-.303	.166		

Correlation Matrix

		X7	X8	X9	X11	X12	X13	X14
Step 8	X7	1.000	.265	-.093	-.597	-.011		.039
	X8	.265	1.000	-.597	-.149	-.070		-.099
	X9	-.093	-.597	1.000	-.054	.024		-.224
	X11	-.597	-.149	-.054	1.000	-.015		-.007
	X12	-.011	-.070	.024	-.015	1.000		-.141
	X14	.039	-.099	-.224	-.007	-.141		1.000
	X18	.086	.027	.060	-.034	.081		.153
	X19	-.057	.037	-.270	.140	.007		.051
	X20	-.159	-.252	-.351	.257	-.224		.007
Step 9	Constant	-.167	-.055	.084	-.036	-.071		-.175
	X2	-.160	-.100	-.009	.184	-.026		.054
	X3	.184	.008	-.056	-.209	.043		-.309
	X4	-.011	-.193	.015	.061	-.032		.184
	X7	1.000	.265	-.098	-.598	-.011		.041
	X8	.265	1.000	-.593	-.153	-.071		-.095
	X9	-.098	-.593	1.000	-.029	.017		-.223
	X11	-.598	-.153	-.029	1.000	-.022		-.011
	X12	-.011	-.071	.017	-.022	1.000		-.133
	X14	.041	-.095	-.223	-.011	-.133		1.000
	X18	.061	.042	-.039	.017	.091		.175
	X20	-.155	-.248	-.362	.250	-.227		.004
Step 10	Constant	-.308	-.039	.139	-.057	.038		-.037
	X2	-.159	-.105	-.013	.191	-.022		.075
	X3	.185	.013	-.059	-.207	.048		-.310
	X4	-.008	-.196	.018	.058	-.033		.179
	X7	1.000	.264	-.096	-.603	-.012		.034
	X8	.264	1.000	-.596	-.156	-.072		-.103
	X9	-.096	-.596	1.000	-.032	.020		-.211
	X11	-.603	-.156	-.032	1.000	-.027		-.015
	X12	-.012	-.072	.020	-.027	1.000		-.151
	X14	.034	-.103	-.211	-.015	-.151		1.000
	X20	-.158	-.247	-.362	.260	-.229		.010
Step 11	Constant	-.310	-.037	.128	-.048			-.024
	X2	-.159	-.104	-.012	.183			.074
	X3	.185	.013	-.059	-.207			-.303
	X4	-.005	-.202	.026	.048			.166
	X7	1.000	.253	-.085	-.604			.033
	X8	.253	1.000	-.588	-.142			-.132
	X9	-.085	-.588	1.000	-.040			-.200
	X11	-.604	-.142	-.040	1.000			-.025
	X14	.033	-.132	-.200	-.025			1.000

Correlation Matrix

		Constant	X1	X2	X3	X4	X5	X6
Step 11	X20	-.236		.154	.103	.082		
Step 12	Constant	1.000		-.403	-.148	-.673		
	X2	-.403		1.000	-.618	.230		
	X3	-.148		-.618	1.000	-.079		
	X4	-.673		.230	-.079	1.000		
	X7	-.362		-.144	.203	.008		
	X8	-.112		-.059	.037	-.189		
	X9	.059		.027	-.010	.081		
	X11	.023		.160	-.246	.019		
	X14	-.031		.074	-.305	.169		
Step 13	Constant	1.000		-.340	-.274			
	X2	-.340		1.000	-.627			
	X3	-.274		-.627	1.000			
	X7	-.485		-.156	.222			
	X8	-.339		-.008	.025			
	X9	.174		-.007	-.005			
	X11	.041		.166	-.258			
	X14	.094		.061	-.297			
Step 14	Constant	1.000		-.332	-.271			
	X2	-.332		1.000	-.645			
	X3	-.271		-.645	1.000			
	X7	-.485		-.168	.241			
	X8	-.314		-.014	-.017			
	X9	.192		.014	-.066			
	X11	.039		.171	-.265			

Correlation Matrix

		X15	X16	X17	X18	X19	X20
Step 8	X7				.086	-.057	-.159
	X8				.027	.037	-.252
	X9				.060	-.270	-.351
	X11				-.034	.140	.257
	X12				.081	.007	-.224
	X14				.153	.051	.007
	X18				1.000	-.327	-.116
	X19				-.327	1.000	.119
	X20				-.116	.119	1.000
Step 9	Constant				-.936		-.019
	X2				-.088		.160
	X3				-.022		.089
	X4				.016		.088
	X7				.061		-.155
	X8				.042		-.248
	X9				-.039		-.362
	X11				.017		.250
	X12				.091		-.227
	X14				.175		.004
	X18				1.000		-.072
	X20				-.072		1.000
Step 10	Constant						-.246
	X2						.159
	X3						.087
	X4						.091
	X7						-.158
	X8						-.247
	X9						-.362
	X11						.260
	X12						-.229
	X14						.010
	X20						1.000
Step 11	Constant						-.236
	X2						.154
	X3						.103
	X4						.082
	X7						-.165
	X8						-.256
	X9						-.392
	X11						.266
	X14						-.025

Correlation Matrix

		X7	X8	X9	X11	X12	X13	X14
Step 11	X20	-.165	-.256	-.392	.266			-.025
Step 12	Constant	-.362	-.112	.059	.023			-.031
	X2	-.144	-.059	.027	.160			.074
	X3	.203	.037	-.010	-.246			-.305
	X4	.008	-.189	.081	.019			.169
	X7	1.000	.216	-.160	-.594			.029
	X8	.216	1.000	-.787	-.075			-.150
	X9	-.160	-.787	1.000	.052			-.210
	X11	-.594	-.075	.052	1.000			-.021
	X14	.029	-.150	-.210	-.021			1.000
Step 13	Constant	-.485	-.339	.174	.041			.094
	X2	-.156	-.008	-.007	.166			.061
	X3	.222	.025	-.005	-.258			-.297
	X7	1.000	.230	-.175	-.593			.029
	X8	.230	1.000	-.793	-.080			-.120
	X9	-.175	-.793	1.000	.066			-.230
	X11	-.593	-.080	.066	1.000			-.021
	X14	.029	-.120	-.230	-.021			1.000
Step 14	Constant	-.485	-.314	.192	.039			
	X2	-.168	-.014	.014	.171			
	X3	.241	-.017	-.066	-.265			
	X7	1.000	.234	-.166	-.591			
	X8	.234	1.000	-.849	-.083			
	X9	-.166	-.849	1.000	.042			
	X11	-.591	-.083	.042	1.000			

Correlation Matrix

		X15	X16	X17	X18	X19	X20
Step 11	X20						1.000
Step 12	Constant						
	X2						
	X3						
	X4						
	X7						
	X8						
	X9						
	X11						
	X14						
Step 13	Constant						
	X2						
	X3						
	X7						
	X8						
	X9						
	X11						
	X14						
Step 14	Constant						
	X2						
	X3						
	X7						
	X8						
	X9						
	X11						

Descriptives

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Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic
Age of the Applicant	202	1	5	2.86	.978
Type of Employment	202	1	3	1.35	.537
Type of Occupation	202	0	10	5.81	2.592
Office Telephone	202	0	1	.82	.384
Home Telephone	202	0	1	.94	.237

Descriptive Statistics

	Skewness	
	Statistic	Std. Error
Age of the Applicant	.121	.171
Type of Employment	1.199	.171
Type of Occupation	-.002	.171
Office Telephone	-1.694	.171
Home Telephone	-3.756	.171

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic
Number of Dependents	202	0	11	3.19	1.445
Purpose of the Loan	202	1	3	1.43	.703
Total Cost of the Project	202	200000	16758409	3176265.94	2689076.616
Loan Amount Requested	202	100000	12500000	1596676.98	1965545.063
Other Sources of Finance	202	0	6500000	1579588.96	1207705.552
Stage of the Project	202	0	4	1.90	1.316
Total Assets of the Applicant	202	0	75500000	4903317.65	8745555.996
Total Liabilities of the Applicant	202	0	4076000	164081.36	571992.030
Monthly Income (Self)	202	6500	360000	53072.63	60945.302
Monthly Income (Spouse)	202	0	135000	7206.28	15754.989
Total Monthly Income (Self and Spouse)	202	12000	360000	60526.44	60387.460
Applicant Equity (%)	202	0	95	51.16	17.448
Rate of Interest Charged	202	8	12	9.35	.654
Loan Duration (yrs)	202	1	4	2.40	.774
Property Value	202	707570	27220000	4297309.70	4050091.198
Quality of the Loan	202	0	1	.83	.379
Valid N (listwise)	202				

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.424	19	.180	1.285	.197[a]
	Residual	25.512	182	.140		
	Total	28.936	201			

a. Predictors: (Constant), Property Value, Stage of the Project, Office Telephone, Rate of Interest Charged, Monthly Income (Spouse), Applicant Equity (%), Age of the Applicant, Total Liabilities of the Applicant, Home Telephone, Type of Occupation, Loan Duration (yrs), Number of Dependents, Total Assets of the Applicant, Type of Employment, Purpose of the Loan, Total Monthly Income (Self and Spouse), Other Sources of Finance, Loan Amount Requested, Monthly Income (Self)

b. Dependent Variable: Quality of the Loan

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	1.112	.465		2.393
	Age of the Applicant	.020	.030	.051	.669
	Type of Employment	.089	.062	.126	1.421
	Type of Occupation	-.019	.013	-.129	-1.453
	Office Telephone	-.068	.082	-.069	-.832
	Home Telephone	.015	.121	.009	.121
	Number of Dependents	.008	.021	.030	.379
	Purpose of the Loan	-.113	.050	-.209	-2.271
	Loan Amount Requested	4.005E-8	.000	.207	1.381
	Other Sources of Finance	-6.207E-8	.000	-.198	-1.568
	Stage of the Project	.045	.027	.157	1.677
	Total Assets of the Applicant	3.165E-9	.000	.073	.823
	Total Liabilities of the Applicant	2.616E-8	.000	.039	.500
	Monthly Income (Self)	-4.322E-6	.000	-.694	-.500
	Monthly Income (Spouse)	-2.691E-6	.000	-.112	-.307
	Total Monthly Income (Self and Spouse)	3.351E-6	.000	.533	.387
	Applicant Equity (%)	.001	.003	.052	.414
	Rate of Interest Charged	-.032	.045	-.056	-.727
	Loan Duration (yrs)	.033	.040	.067	.821
	Property Value	-8.202E-9	.000	-.088	-.746

a. Dependent Variable: Quality of the Loan

Coefficients[a]

Model		Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	.018		
	Age of the Applicant	.504	.819	1.220
	Type of Employment	.157	.619	1.615
	Type of Occupation	.148	.619	1.615
	Office Telephone	.406	.701	1.426
	Home Telephone	.904	.846	1.182
	Number of Dependents	.705	.751	1.332
	Purpose of the Loan	.024	.570	1.754
	Loan Amount Requested	.169	.215	4.659
	Other Sources of Finance	.119	.305	3.278
	Stage of the Project	.095	.551	1.816
	Total Assets of the Applicant	.411	.617	1.621
	Total Liabilities of the Applicant	.618	.778	1.286
	Monthly Income (Self)	.618	.003	398.791
	Monthly Income (Spouse)	.759	.036	27.407
	Total Monthly Income (Self and Spouse)	.699	.003	392.344
	Applicant Equity (%)	.679	.308	3.243
	Rate of Interest Charged	.468	.822	1.216
	Loan Duration (yrs)	.413	.721	1.387
	Property Value	.457	.351	2.845

a. Dependent Variable: Quality of the Loan

Excluded Variables[b]

Model	Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance

a. Predictors in the Model: (Constant), Property Value, Stage of the Project, Office Telephone, Rate of Interest Charged, Monthly Income (Spouse), Applicant Equity (%), Age of the Applicant, Total Liabilities of the Applicant, Home Telephone, Type of Occupation, Loan Duration (yrs), Number of Dependents, Total Assets of the Applicant, Type of Employment, Purpose of the Loan, Total Monthly Income (Self and Spouse), Other Sources of Finance, Loan Amount Requested, Monthly Income (Self)

b. Dependent Variable: Quality of the Loan

Classification Table[a]

Observed			Predicted: Quality of the Loan: Default/Bad Credit	Predicted: Quality of the Loan: No Default/Good Credit
Step 1	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	25	142
		Overall Percentage		
Step 2	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	25	142
		Overall Percentage		
Step 3	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	25	142
		Overall Percentage		
Step 4	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	24	143
		Overall Percentage		
Step 5	Quality of the Loan	Default/Bad Credit	16	19
		No Default/Good Credit	27	140
		Overall Percentage		
Step 6	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	28	139
		Overall Percentage		
Step 7	Quality of the Loan	Default/Bad Credit	16	19
		No Default/Good Credit	25	142
		Overall Percentage		
Step 8	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	26	141
		Overall Percentage		
Step 9	Quality of the Loan	Default/Bad Credit	15	20
		No Default/Good Credit	28	139
		Overall Percentage		
Step 10	Quality of the Loan	Default/Bad Credit	16	19
		No Default/Good Credit	29	138
		Overall Percentage		
Step 11	Quality of the Loan	Default/Bad Credit	16	19
		No Default/Good Credit	29	138
		Overall Percentage		

a. The cut value is .750

Classification Table[a]

Observed			Predicted: Quality of the Loan: Percentage Correct
Step 1	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	85.0
		Overall Percentage	77.7
Step 2	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	85.0
		Overall Percentage	77.7
Step 3	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	85.0
		Overall Percentage	77.7
Step 4	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	85.6
		Overall Percentage	78.2
Step 5	Quality of the Loan	Default/Bad Credit	45.7
		No Default/Good Credit	83.8
		Overall Percentage	77.2
Step 6	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	83.2
		Overall Percentage	76.2
Step 7	Quality of the Loan	Default/Bad Credit	45.7
		No Default/Good Credit	85.0
		Overall Percentage	78.2
Step 8	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	84.4
		Overall Percentage	77.2
Step 9	Quality of the Loan	Default/Bad Credit	42.9
		No Default/Good Credit	83.2
		Overall Percentage	76.2
Step 10	Quality of the Loan	Default/Bad Credit	45.7
		No Default/Good Credit	82.6
		Overall Percentage	76.2
Step 11	Quality of the Loan	Default/Bad Credit	45.7
		No Default/Good Credit	82.6
		Overall Percentage	76.2

a. The cut value is .750

Classification Table[a]

Observed			Predicted: Quality of the Loan: Default/Bad Credit	Predicted: Quality of the Loan: No Default/Good Credit
Step 12	Quality of the Loan	Default/Bad Credit	16	19
		No Default/Good Credit	30	137
		Overall Percentage		
Step 13	Quality of the Loan	Default/Bad Credit	14	21
		No Default/Good Credit	23	144
		Overall Percentage		
Step 14	Quality of the Loan	Default/Bad Credit	14	21
		No Default/Good Credit	20	147
		Overall Percentage		

a. The cut value is .750

Classification Table[a]

Observed			Predicted: Quality of the Loan: Percentage Correct
Step 12	Quality of the Loan	Default/Bad Credit	45.7
		No Default/Good Credit	82.0
		Overall Percentage	75.7
Step 13	Quality of the Loan	Default/Bad Credit	40.0
		No Default/Good Credit	86.2
		Overall Percentage	78.2
Step 14	Quality of the Loan	Default/Bad Credit	40.0
		No Default/Good Credit	88.0
		Overall Percentage	79.7

a. The cut value is .750

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